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PAPER

Computational Neuroscience in Higher Education: A Systematic Review on the Problems Addressed, Methods Used and Implications

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ABSTRACT

Computational neuroscience (CNS) has enabled significant advances in the understanding of cognitive processes through mathematical models and computational simulations, providing a more precise understanding of brain activity. However, its application in higher education remains limited, which restricts its potential to optimize teaching, cognitive and emotional regulation, and personalized learning. This study aims to examine the problems addressed by CNS, the methods used, and their implications for higher education, analyzing scientific articles from the ScienceDirect, PubMed, and Scopus databases through a systematic review study following the PRISMA guidelines. The results show that the application of methods such as EEG, BCI, neurofeedback, fNIRS, tDCS, and computational models has facilitated the adaptation of content and the assessment of cognitive load in students. However, its implementation still faces methodological, economic, and technological barriers, such as variability in neural responses and limited accessibility. It is concluded that CNS has a high potential to transform higher education, but its effective integration requires the adoption of regulatory and standardized frameworks, which promote the creation of specialized areas in CNS within their departments of psychopedagogy or neuroeducation, in order to promote its development, accessibility, and ethical application in educational environments.

KEYWORDS

computational neuroscience, higher education, neurofeedback, brain-computer-interface, systematic review

1 INTRODUCTION

Neuroscience has emerged as a key field in higher education, providing a solid theoretical framework for understanding the relationship between neuronal activity and the cognitive processes involved in knowledge acquisition [1]. By analyzing

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the mechanisms underlying learning, memory, and decision-making, this discipline offers fundamental tools for optimizing educational strategies tailored to the individual characteristics of students [2]. The integration of computational models in the educational field has allowed the identification of neural patterns associated with key cognitive functions, which reinforces the scientific basis for the development of evidence-based pedagogical approaches [3]. The convergence between neuroscience and information technologies has facilitated the implementation of adaptive methodologies that favor the personalization of learning and improve students' ability to process information efficiently [4]. In this context, it has been argued that the use of neurocomputational models not only contributes to a better understanding of cognitive dynamics in educational environments but also allows for the identification of more efficient pedagogical strategies in university teaching [5]. Recent studies have demonstrated the positive impact of these models in optimizing learning processes, highlighting the development of pedagogical tools based on neural simulations that improve information retention and processing [6].

The rise of emotional and cognitive disorders in higher education has increased interest in neuroscience as a key discipline to address the challenges in students' mental health. Neural plasticity is a fundamental principle that explains how academic and emotional experiences can modify brain architecture, influencing the ability to adapt and psychological well-being [7]. In this sense, emotional regulation is a critical process that intervenes in the adaptation to the university environment and whose alteration can generate maladaptive responses, such as anxiety and chronic stress, which affect academic performance and decision-making [8]. CNS has allowed modeling and predicting neural patterns linked to emotional disorders such as anxiety and depression, offering innovative tools for the evaluation and treatment of these disorders through neurocomputational simulations and machine learning algorithms [9]. Likewise, the influence of the digital environment in the virtual learning process has generated new challenges in mental health, evidencing the need for strategies that mitigate the impact of academic stress on students [10]. In this line, the neuroscientific approach in higher education not only seeks to improve learning processes but also the implementation of methodologies that favor emotional regulation and student well-being [11].

The human brain is the most sophisticated information processing system known, capable of integrating, interpreting, and responding to stimuli in real time within a dynamic environment [12]. Its functioning does not depend solely on individual neuronal activity but also on the interaction of complex networks that model patterns of behavior, learning, and decision-making [13]. In this context, CNS has emerged as an interdisciplinary field that mathematically formalizes these processes, allowing the simulation and prediction of neurobiological phenomena through models based on artificial intelligence and applied mathematics [14]. Since its origin in the 1980s, this discipline has evolved by integrating theories of neuroscience, computing, and machine learning to decipher the principles of brain processing and its relationship with cognition [15]. Currently, CNS is considered not only to facilitate the understanding of fundamental neural mechanisms but also to provide innovative tools for the study of complex cognitive functions and their applications in different scientific and technological fields [16].

From the CNS perspective, mental activity is modeled from specific computational processes implemented in the brain, allowing the analysis of cognitive phenomena and their relationship with neural architecture [17]. Within this framework, theories such as the Bayesian brain have been developed, which postulate that the nervous system processes information in a probabilistic manner, constantly updating internal models based on error prediction and correction [18]. Computational modeling of the brain has allowed the identification of neural activity patterns underlying perception and decision-making, using approaches that combine neuroimaging and artificial neural networks to interpret the dynamics of cognition [19]. Furthermore, the use of computational models has also facilitated the identification of individual differences in neural processing, providing analytical tools to assess variations in the brain mechanisms underlying different cognitive and emotional states [20]. These methodologies have revolutionized the understanding of mental processes, offering a unified approach that integrates principles of predictive inference and computational representation of sensory information [21].

In this context, the present study aims to carry out a systematic review of the literature on the contribution of CNS in higher education, with the purpose of identifying the problems addressed, their areas of application, and the implications of their implementation in the university environment. Through a mixed approach, which combines qualitative and quantitative analysis, this study seeks to characterize and evaluate the contribution of CNS in the optimization of teaching-learning processes, emotional regulation, and cognitive well-being of university students. The exploratory scope of the research allows us to investigate the way in which this discipline has been used to solve educational challenges, while the descriptive scope enables the systematic organization of existing knowledge, facilitating the identification of gaps and opportunities for future research. Based on the above, the research answers three fundamental questions: (RQ1) What are the problems addressed by CNS in higher education?; (RQ2) What are the methods of CNS that have been applied in higher education?; and (RQ3) What are the implications of applying CNS in higher education? Based on these questions, this systematic review seeks not only to map the state of the art but also to provide an analytical framework to guide the design of future strategies for the effective integration of neurocomputational models in higher education.

2 CONCEPTUAL FRAMEWORK

2.1 Computational neuroscience

Computational neuroscience is an interdisciplinary field that combines principles of neuroscience, mathematics, and computing to analyze and predict the behavior of the nervous system [22]. Its main purpose is to understand how electrical and chemical signals generated in the brain are processed, stored, and transmitted to give rise to cognitive and behavioral functions. Through computational models, this discipline allows the simulation of neurobiological processes and the examination of neuronal behavior in response to different stimuli, providing fundamental tools for the study of cognition and brain plasticity [23]. The study of CNS is linked to various branches of neuroscience, including cognitive neuroscience, social neuroscience, clinical neuroscience, developmental neuroscience, affective neuroscience, and behavioral neuroscience [24]. Each of these specialties addresses different aspects of the nervous system and its relationship with human behavior. For example, cognitive neuroscience studies the neural mechanisms that support processes such as memory, learning, and decision making, while affective neuroscience analyzes the influence of brain structures and neural networks on emotional regulation and affective states [25].

From a computational perspective, multiple models have been developed that allow the representation of brain activity and the simulation of neuronal dynamics in various scenarios, such as learning and emotional regulation. These include artificial neural networks, designs to replicate the behavior of biological networks, and models inspired by Bayesian theory, which interpret information processing in terms of probabilities, facilitating the prediction of brain responses to stimuli [26]. A fundamental concept in CNS is the linear superposition model, which postulates that the activation of a neuron in a receptive field is equivalent to the sum of the responses generated by the stimuli applied within said field [22]. This principle explains how neurons integrate sensory information and respond to multiple signals within a neural network. Figure 1 shows a schematic representation of this model, where it can be seen that the total response of a neuron to various stimuli is the combination of each individual response within the receptive field [26].

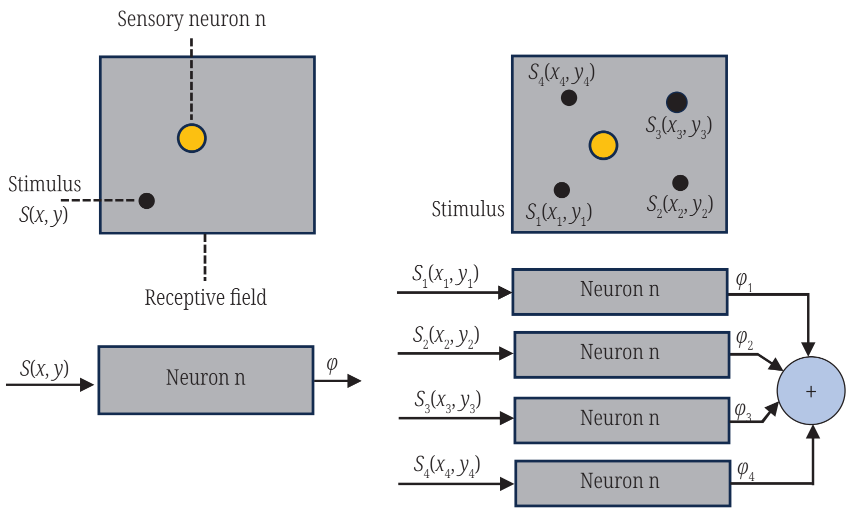

Fig. 1. Linear superposition model

According to this model, the neuronal receptive field is the region in which different stimuli $S(x, y)$ are processed by a set of interconnected neurons. Each one responds through an activation function (φ), whose combination determines the resulting action potential (R). This model is crucial in CNS since it allows us to understand how neurons integrate information in learning and decision-making processes. Equation 1 [26] represents the total neuronal response R, as the sum of the individual responses φ_i generated by stimuli $S(x, y)$ applied in different positions of the receptive field.

$$R = \sum_{i}^{n} \varphi_i \tag{1}$$

Furthermore, another relevant feature of the model is the proportionality of the neuronal response with respect to the intensity of the stimulus, which is expressed by equation 2 [26].

$$R = \propto {}^{*} \varphi \tag{2}$$

Where, $\propto$ is a proportionality coefficient that presents the modulation of the neuronal response as a function of the magnitude received. This principle is essential in CNS, as it allows modeling how neuronal activity adjusts based on the strength of the sensory input and its impact on perception, cognition, and learning [26].

3 METHODOLOGY

3.1 Focus and scope

In this systematic review study on CNS in higher education, a mixed approach is adopted, combining a qualitative analysis to examine and synthesize the content of the articles and a quantitative analysis to determine the prevalence of the problems addressed and their categorization. Likewise, the scope of the research is exploratory and descriptive. It is exploratory because it seeks to investigate and characterize the problems that computational neuroscience has addressed in higher education, with the purpose of identifying gaps and research opportunities. It is descriptive because it allows organizing and classifying the available information, providing a detailed view of how this discipline has been applied in the university setting. Unlike other studies focused on the description of neuroscientific technologies, this systematic review focuses on the implications of computational neuroscience in higher education, examining its application in improving problems associated with teaching-learning processes, mental health and emotional regulation, as well as cognitive regulation in university students.

3.2 Search strategy

In this systematic review, an exhaustive search of scientific literature was carried out with the aim of identifying relevant studies that answer the research questions, avoiding generating biases in the results of the study. For these, key terms in English were selected that represent fundamental concepts, such as "computational neuroscience," "brain-computer-interface," "Neurofeedback," "fNIRS," "EEG," "higher education," "university learning," "cognitive regulation," "emotional regulation," "adaptative regulation," and "adaptative learning." These terms were strategically combined using Boolean operators in order to optimize the precision and coverage of the search.

The studies were collected from three high-impact databases in computational neuroscience and higher education: Scopus, ScienceDirect, and PubMed. Scopus was selected for its broad scope in interdisciplinary research on education and technology. ScienceDirect was included for its focus on applied neuroscience and computational learning. PubMed was incorporated to identify studies on neurotechnology such as EEG, fNIRS, neurofeedback, and non-invasive brain stimulation, allowing the analysis of their impact on learning, cognitive and emotional regulation in various study populations.

In order to delimit the selection of articles that would subsequently be subjected to an exhaustive content review process, specific inclusion and exclusion criteria were established; these criteria ensure methodological relevance and thematic coherence [27]. Table 1 shows four inclusion criteria and their corresponding exclusion criteria, ensuring methodological coherence and alignment. These criteria focus on the study population in which CNS was applied, the type of scientific document to be considered, the time interval of publication, and access to the full content of the research.

Table 1. Inclusion and exclusion criteria

Criteria	Detail
Inclusion	**1.** Studies that apply computational neuroscience in higher education. **2.** Scientific articles published in scientific journals and peer reviewed. **3.** Scientific articles were published between 2014 and 2024. **4.** Open access scientific articles.
Exclusion	**1.** Research conducted in populations outside higher education, such as primary or secondary school students. **2.** Scientific publications such as these, books, book chapters, conference papers, letters to editors. **3.** Scientific articles were published before 2014 and after 2024. **4.** Scientific articles with access restrictions.

3.3 Data extraction

The data extraction process was carried out following the PRISMA methodology, adapted to this systematic review study of Computational Neuroscience in Higher Education, according to the format developed by [28], [29]. The collection of studies was carried out on February 5, 2025, in three databases, Scopus (n = 1126), ScienceDirect (n = 308), and PubMed (n = 267), obtaining an initial total of 1701 documents. In the identification phase, the requested studies and those published outside the time range 2014 to 2024 were excluded, reducing the total number of documents to 1449. In the projection phase, the titles and abstracts were reviewed, which led to the exclusion of 1023 articles that were not directly related to the research, leaving 429 studies under evaluation. In the eligibility phase, the previously defined inclusion and exclusion criteria were applied, resulting in the elimination of 403 studies that did not meet the established requirements. Finally, in the inclusion phase, the bias assessment criterion proposed in the research developed by [30] was used to select the final scientific articles. As a result, 4 scientific articles that did not reach the minimum quality threshold were discarded, obtaining a total of 22 studies for the analysis and synthesis of results. Figure 2 shows the data extraction sequence based on the PRISMA guideline.

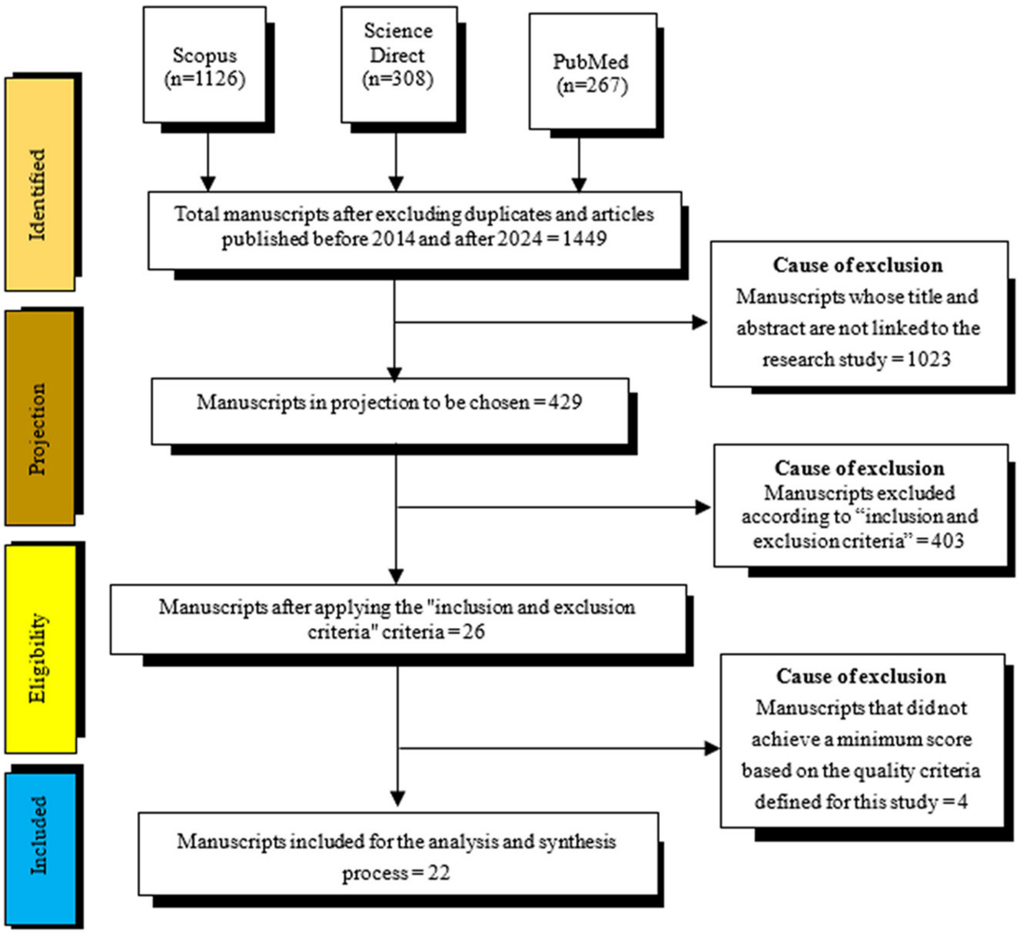

Fig. 2. Data extraction sequence based on the PRISMA guideline

3.4 Quality analysis of eligible articles

For the quality analysis of the eligible articles, four criteria were established that define the quality (CQ) of the articles to be included for the content analysis and synthesis phase. Criterion CQ1 implies that the scientific article details the problems addressed with CNS in higher education; criterion CQ2 implies that the scientific article details the methods of CNS applied in the university environment, and criterion CQ3 implies that the scientific article specifies the implications of the use of CNS in higher education. In this sense, Table 2 shows the results of the quality analysis, in which a score of one represents a low quality of the chosen study, three implies that the study as a whole does not meet the criterion, and a score of five implies that the chosen study completely meets the criterion.

Table 2. Results of the quality analysis of the studies eligible for the systematic review

Reference	CQ1	CQ2	CQ3	Total	Condition of the Scientific Article
[31]	5	5	5	100%	Including
[32]	5	5	5	100%	Including
[33]	5	5	5	100%	Including
[34]	5	5	5	100%	Including
[35]	5	5	5	100%	Including
[36]	5	5	5	100%	Including
[37]	1	1	1	20%	Excluded
[38]	5	5	5	100%	Including
[39]	5	5	5	100%	Including
[40]	5	3	5	87%	Including
[41]	1	1	1	20%	Excluded
[42]	5	5	5	100%	Including
[43]	5	5	5	100%	Including
[44]	5	5	5	100%	Including
[45]	5	5	5	100%	Including
[46]	5	5	5	100%	Including
[47]	5	5	5	100%	Including
[48]	5	3	5	87%	Including
[49]	3	5	5	87%	Including
[50]	5	5	5	100%	Including
[51]	5	5	5	100%	Including
[52]	1	1	1	20%	Excluded
[53]	1	1	1	20%	Excluded
[54]	5	5	5	100%	Including
[55]	5	5	5	100%	Including
[56]	5	5	5	100%	Including

4 RESULTS

4.1 What are the problems addressed by computational neuroscience in higher education?

Regarding the problems addressed by computational neuroscience in higher education, the analysis of the scientific articles included in this systematic review, which covers publications between 2014 and 2024, allowed us to identify three main categories of problems addressed in literature. These findings show that computational neuroscience has been predominantly applied in the university setting to solve problems related to "Teaching-learning processes," "Mental health and emotional regulation," and "Cognitive regulation." The classification of the studies reflects a growing trend towards the integration of neuroscientific technologies in higher education, with the aim of optimizing learning, personalizing instruction, and improving academic accessibility. Various studies have explored the impact of computational neuroscience in environments such as MOOCs, STEM programs, and intelligent tutoring models, evaluating brain activity in response to different pedagogical strategies. The application of brain-computer interfaces (BCI) for the detection and classification of dyslexia has also been addressed, facilitating a more precise diagnosis and personalized support for students with learning difficulties. In addition, the effects of sleep deprivation on academic performance have been investigated, highlighting the role of interpersonal brain synchronization in compensating for learning deficits. Table 3 shows the result of the categorization of the problems addressed in the reviewed literature.

Table 3. Categorization of the problems addressed in the reviewed literature

Category	Description	Reference
Mental health issues and emotional regulation	The problem of anxiety in students was addressed through the use of neurofeedback, allowing the reduction of stress levels through the modulation of brain activity.	[31]
	The use of BCI in the measurement of emotional variables (stress, concentration, relaxation) during interaction with augmented reality books is explored, evaluating its impact on the personalization of pedagogical strategies.	[43]
	The impact of Neuroelectrophysiology on emotional regulation was evaluated by using EEG to analyze changes in brain rhythms associated with meditation and relaxation techniques.	[44]
	Hyperscanning with fNIRS was applied to analyze brain synchronization between expert and novice teachers, evidencing differences in emotional regulation during collaborative tasks.	[46]
	Machine learning was implemented to detect mental stress in students, using physiological data analysis and stress surveys to identify anxiety levels.	[47]
	Emotion recognition was assessed through EEG in intelligent tutoring environments (ITS), allowing the adaptation of educational materials based on the students' level of engagement.	[48]
	Hemoencephalography (HEG) was applied to evaluate prefrontal activity and its relaxation with emotional regulation and decision making in university students, providing tools for the early detection of anxiety and depression.	[55]
	The impact of brain synchronization on reducing math anxiety was evaluated through the use of BCI in educational games.	[56]

(Continued)

Table 3. Categorization of the problems addressed in the reviewed literature *(Continued)*

Category	Description	Reference
Problems associated with the teaching-learning processes	Personalization of learning was addressed through computational analysis of neurophysiological variables with AI, allowing for the adaptation of educational content.	[32]
	The aim was to address the early detection of difficulties in phonological processing in students of English as a second language by using fNIRS to analyze the relationship between advanced mathematical thinking and language processing.	[33]
	The optimization of teaching in natural sciences and engineering was addressed through Brain-Based Instruction (BBI), applying neuroscientific principles to improve learning retention and construction.	[34]
	A virtual reality tool (VRBrain) based on magnetic resonance imaging (MRI) was implemented for teaching neuroanatomy, facilitating three-dimensional exploration of the brain.	[38]
	Training in cognitive psychophysiology was strengthened through open science, with EEG databases, open-source software and accessible educational materials to improve the analysis of brain activity in cognitive processes.	[42]
	Neural engagement with educational videos was analyzed using EEG, employing intersubject correlation (ISC) to predict information retention and optimize the design of digital resources.	[49]
	The use of Computational Neuroscience in interdisciplinary Neuroscience teaching was investigated, integrating computational model-based approaches into the engineering curriculum.	[50]
	The use of EEG was applied to assess mental effort in online learning environments (MOOCs) and provide automatic feedback to improve self-regulation of learning.	[51]
	fNIRS was used to assess prefrontal cortex activity in teaching-learning interactions, measuring neural synchronization in video game-based tasks.	[53]
Problems associated with cognitive regulation	Dyslexia detection in students was sought using BCI and interactive linguistic tools, using EEG and machine learning to identify brain patterns associated with difficulties in language processing.	[35]
	The optimization of academic performance was explored by combining transcranial direct current stimulation (tDCS) and neurofeedback to improve declarative memory and cerebral blood flow.	[36]
	The impact of interpersonal brain synchronization (IBS) between instructors and students in compensating for learning deficits caused by sleep deprivation was examined.	[39]
	The relationship between educational diversity and group creativity was explored using fNIRS hyperscanning, assessing brain synchronization in group interactions.	[40]
	The efficacy of frontal-medial theta neurofeedback training (FM theta NFT) in improving episodic memory and cognitive control in learning tasks was investigated.	[45]

From a quantitative point of view, the reviewed studies show that the category with the greatest representation in literature corresponds to problems associated with the teaching-learning process, covering 40.91% of the total studies. This percentage represents that the main application of CNS in higher education has been the optimization of teaching methodologies through advanced neuroscientific tools. On the other hand, mental health problems and emotional regulation constitute the second most addressed category, with 36.36% of the studies. These indicate an interest in understanding how emotional factors, such as anxiety and stress, affect academic performance, using neuroscientific approaches to evaluate and improve emotional regulation in university students. Finally, problems associated with cognitive regulation represent 22.73% of the studies included in the review. This group of research has mainly explored the interaction between brain activity and cognitive performance, addressing aspects such as working memory, attention, and information processing in higher education students. Figure 3 shows the percentage distribution of studies by category of problems addressed.

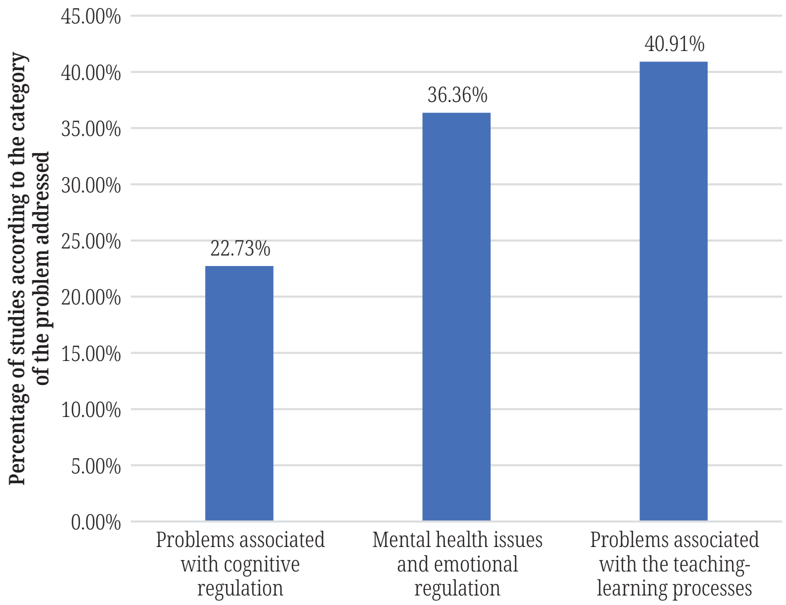

Fig. 3. Percentage distribution of reviewed studies by category of problem addressed

4.2 What are the methods of computational neuroscience that are being applied in the field of higher education?

Based on the findings obtained in this systematic review, a growing integration of various CNS methods in higher education is identified, applied in the study of cognition, emotional regulation, and learning optimization. Among the most frequent methods addressed are EEG, fNIRS, and BCI, which represent an emphasis on the evaluation of neuronal activity in real time and its relationship with educational processes. EEG has been used to measure brain activity in university students, evaluate cognitive load in digital environments, and analyze the relationship between attention and information retention [31], [38], [42], [43], [48], [49], [51]. In addition, its integration with neurofeedback has allowed the design of interventions to improve working memory and emotional regulation, optimizing academic performance [31], [36], [45]. Although less widely used than EEG, fNIRS has proven to be a relevant tool in higher education, with applications in the assessment of brain activity during decision-making and in neuronal synchronization in collaborative environments [39], [40], [46]. It has been used in studies on cognitive load in problem solving, allowing the analysis of functional connectivity in students and the way they process information in group activities [33], [54]. Furthermore, it has been integrated with innovative educational methodologies, such as the use of interactive tools in the teaching of neuroanatomy, where fNIRS and EEG have been used to assess brain activity during the exploration of three-dimensional models [38]. On the other hand, BCI interfaces have been applied with greater emphasis in the field of educational accessibility, highlighting their use in the early detection of dyslexia and in the analysis of emotional responses to learning [35], [56]. In recent studies, the combination of BCI and EEG has been used to measure the emotional impact of interaction with books in augmented reality format, evaluating how these technologies can influence students' concentration and motivation [43]. Other, less used methods are those based on computational learning models, which have been explored in higher education through the use of artificial neural networks and machine learning algorithms to personalize pedagogical strategies and predict academic performance

[32], [47]. Likewise, early brain stimulation (HEG) and noninvasive brain stimulation (tDCS) have been used to analyze emotional regulation and decision-making in university students, allowing students to evaluate the impact of academic stress on neuronal activity and the effect of stimulation on the optimization of executive function [36], [55]. Overall, the results show that NSS in higher education has been predominantly applied to the measurement of brain activity and educational accessibility, while approaches oriented to neuronal stimulation or learning modeling are still in an exploratory phase. These findings suggest a significant potential for the implementation of pedagogical strategies based on neuroscientific evidence, promoting an evolution in educational methodologies towards more personalized approaches integrated with advanced technologies. Table 4 shows the categorization of the applied NSS methods in higher education.

Table 4. Categorization of applied methods of CNS in higher education

Category	Description	Reference
EEG	EEG has been used to measure brain activity in university students, assess cognitive load in online learning environments, and analyze the impact of pedagogical strategies on attention and academic performance.	[31], [38], [42], [43], [48], [49], [51]
fNIRS	fNIRS has been used to measure brain activity during decision making, analyze neuronal synchronization between teachers and students, and evaluate cognitive processes in higher education.	[33], [38], [39], [40], [46], [54]
BCI	BCI devices have been used to analyze emotional responses in learning, evaluate the impact of anxiety on knowledge acquisition, and improve accessibility in students with dyslexia.	[35], [43], [56]
Neurofeedback	Neurofeedback has been applied in higher education to improve working memory, emotional regulation, and concentration in students.	[31], [36], [45],
Computational learning models	Artificial neural networks and machine learning algorithms have been used to personalize pedagogical strategies and detect levels of academic stress in university students.	[32], [47]
Hemoencephalography (HEG) and Brain stimulation	HEG has been used to assess emotional regulation and decision making in college students, as well as non-innovative brain stimulation (tDCS) to improve memory and concentration.	[36], [55]

4.3 What are the implications of applying computational neuroscience in higher education?

Based on the findings obtained regarding the implications derived from the contribution of the CNS in higher education, it was possible to categorize it into two groups: "Positive implications" and "Negative implications." The studies reviewed show that the CNS has allowed the optimization of teaching through the use of tools such as EEG and neurofeedback, facilitating the personalization of learning and improving the retention of information in digital environments. Likewise, BCIs have proven to be effective in detecting learning difficulties, such as dyslexia, while computational models based on machine learning have favored the adaptation of educational content to individual cognitive needs. The integration of brain stimulation techniques such as tDCS and neurofeedback has shown benefits in regulating academic stress and improving working memory, consolidating NC as an interdisciplinary field with direct applications in the optimization of student mental health. In addition, the combination of EEG and fNIRS has allowed the analysis of neuronal synchronization in collaborative environments, providing key information on the interaction between teachers and students. Augmented reality and neuroimaging applied to neuroanatomy teaching have improved the understanding of complex brain structures, facilitating the integration of immersive approaches into academic training. These advances reflect the potential of CNS to transform higher education, allowing for an evidence-based approach that strengthens the understanding of the learning process.

However, despite the observed benefits, the review has also identified methodological and technological challenges that limit the widespread application of CNS in higher education. Variability in students' brain activity makes it difficult to calibrate technologies such as BCI and EEG, generating inconsistencies in results and requiring more robust analysis methodologies. Likewise, accessibility to these tools remains a challenge, given that their implementation involves high costs and the need for specialized training, which restricts their use to institutions with greater resources. The gap between theory and practical application remains a limitation in the academic field, highlighting the need for further teacher training for the effective integration of these technologies in teaching. Furthermore, the use of neurofeedback has shown heterogeneous results depending on the level of training of the students, indicating the need for standardized protocols to ensure its effectiveness. In ethical terms, the collection of neural data raises concerns about privacy and informed consent, especially in the use of BCI in educational studies. Finally, although the combined use of techniques such as tDCS and neurofeedback has shown improvements in cognitive function, their long-term effectiveness still requires further research to assess their impact on academic performance. Table 5 shows the categorization of the implications of CNS in higher education.

Table 5. Categorizing the implications of CNS in higher education

Category	Description	Reference
Positive implication	The application of artificial intelligence in the early detection of emotional crises through big data analysis enables personalized interventions in student mental health.	[32]
	Teaching neuroanatomy through virtual reality improved understanding of the spatial compression of brain structures.	[38]
	Brain synchronization between students and instructors can offset the negative effects of sleep deprivation on learning.	[39]
	Open access to neuroscience data has favored the replicability of studies, strengthened evidence-based neural analysis and promoting interdisciplinary approaches for the development of innovative technologies.	[42]
	Combining meditation techniques can induce changes in brain activity, improving memory and reducing stress.	[44]
	FM theta training using neurofeedback improves memory regulation and cognitive interference.	[45]
	The identification of neural markers of effective interaction between teachers and students can contribute to the development of more personalized pedagogical strategies.	[46]
	Machine learning models can predict stress in students and improve early intervention strategies.	[47]
	Detecting emotional states using EEG in smart tutoring allows adjusting the learning pace.	[48]
	Measuring neural engagement with EEG optimizes the production of online educational materials, improving information retention and academic performance.	[49]
	The integration of computational models in CNS teaching optimized the simulation of neural processes and strengthened the interdisciplinary approach in the analysis of the nervous system.	[50]
	Personalization of learning through EEG in online education facilitates the adaptation of content to individual cognitive needs.	[51]
	The synchronized activation of the left prefrontal cortex in teachers and students during teaching-learning tasks suggests that this neural mechanism is key in the integration of information about the process itself, which has implications for the optimization of educational methodologies.	[53]
	The use of tDCS in educational settings resulted in improvements in emotional regulation and executive function in college students under academic stress.	[55]
	The integration of BCI in computational neuroscience allowed to modulate the neuronal activity associated with mathematical anxiety, evidencing its potential in optimizing cognitive regulation in educational environments.	[56]

Table 5. Categorizing the implications of CNS in higher education *(Continued)*

Category	Description	Reference
Negative implication	The use of neurofeedback suggests benefits in regulating academic stress and improving mental health, but its effectiveness varies between individuals, indicating the need for further studies to optimize its implementation in higher education.	[31]
	Advanced mathematical thinking may interfere with phonological processing in English learners, indicating the need to reorganize the sequence of courses to optimize academic performance.	[33]
	There is a gap between theoretical knowledge and practical application of neuroscience-based teaching in higher education, which highlights the need for teacher training.	[34]
	BCI integration with linguistic software improves dyslexia detection but faces challenges of accessibility and accuracy in EEG signal analysis.	[35]
	The combined use of neurofeedback and transcranial cognitive stimulation (tDCS) can improve memory and reduce cognitive fatigue in students, but its long-term effectiveness requires further research.	[36]
	Academic diversity influences group creativity and neural synchronization, but further studies are required to confirm its impact on higher education.	[40]
	The use of BCI and EEG in education presents methodological challenges due to individual variability in brain responses and the need for personalized calibration.	[43]

5 DISCUSSION

Regarding the results obtained on the problems addressed by CNS in higher education, the findings of this systematic review coincide with the growing trend to use neuroscientific tools to optimize teaching-learning processes, regulate cognition, and improve the mental health of students. In accordance with these results, in the study developed by [57], they highlight that CNS-based technologies have allowed the evaluation of neural patterns in educational environments, facilitating the identification of difficulties in information retention and the design of more effective pedagogical strategies. Likewise, in the work carried out by [58], they underline those interactive technologies, such as neurofeedback and BCI, have proven to be promising in the emotional regulation of students, favoring the reduction of academic stress and the improvement of concentration in digital learning environments. Furthermore, in [59], they highlight the relevance of using fNIRS to analyze brain synchronization in collaborative activities, showing that greater inter-brain connectivity is associated with better academic performance and greater cohesion in group learning. These studies support the applicability of CNS in higher education and reinforce the need to continue exploring its impact in different domains of university learning.

On the other hand, with respect to the results obtained on the CNS methods applied in higher education, there is evidence of a growing implementation of techniques such as EEG, BCI, and fNIRS to analyze neuronal activity in educational contexts. In the same line with the findings, in the study developed by [60], they point out that EEG has been a key tool in the evaluation of cognitive load and attention in university students, allowing them to correlate brain activity patterns with academic performance. Furthermore, in the research of [59], they highlight the impact of fNIRS in the measurement of interpersonal neural synchronization in collaborative learning environments, suggesting that greater synchronization between teachers and students improves knowledge transfer and information retention. Likewise, in the work carried out by [61], they emphasize the use of neurofeedback as an emerging method within the CNS, particularly in the training of social and cognitive skills in students with learning deficits. This evidence reinforces the idea that the application of these methods not only optimizes the teaching-learning processes but also opens new opportunities for the personalization of instruction in higher education.

Finally, regarding the results obtained on the implications of CNS in higher education, it is observed that its integration has generated both significant benefits and challenges that limit its large-scale implementation. In relation to these findings, the study carried out by [62] points out that the convergence between neurosciences and educational technologies has allowed for improved personalization of learning and early detection of cognitive difficulties, which favors accessibility and educational equity. However, the research developed by [63] establishes that the lack of specialized training in the use of CNS tools in the educational field represents an obstacle to its effective application, generating a gap between theoretical knowledge and its implementation in university environments. Likewise, in the work carried out by [64], they emphasize that, although CNS has proven to be useful for evaluating cognitive load and optimizing teaching in digital environments, the collection and analysis of neurophysiological data raise ethical concerns about students' privacy and informed consent. In this context, the implementation of methodologies emerges as a key strategy to maximize their impact on higher education.

6 CONCLUSION

From the findings identified in this systematic review, in studies published from 2014 to 2024, it is evident that CNS has emerged as a key tool in higher education, providing advanced models for learning optimization, cognitive and emotional regulation, and the personalization of pedagogical strategies. The application of methods based on EEG, BCI, neurofeedback, fNIRS, tDCS, and computational models has allowed for the precise analysis of neuronal activity in educational environments, facilitating the adaptation of content and the assessment of cognitive load in students. These advances reflect the impact of CNS in the integration of neuroscientific approaches in teaching, strengthening the interdisciplinarity between neuroscience, education, and artificial intelligence. However, its implementation still faces barriers such as variability in neuronal responses, the need for personalized calibrations, and high infrastructure costs. Furthermore, the collection of neurophysiological data poses challenges in terms of privacy and ethics, while the heterogeneity in the results of techniques such as neurofeedback and tDCS highlights the need for further studies that optimize their use in educational contexts. In this sense, it is concluded that CNS has a high potential to transform higher education, but its effective integration requires the adoption of regulatory and standardized frameworks, which promote the creation of specialized areas in CNS within their psychopedagogy or neuroeducation departments, in order to promote its development, accessibility, and ethical application in educational environments.

7 LIMITATIONS OF THE STUDY

Despite the methodological rigor employed in this systematic review, there are certain limitations that should be considered. First, the selection of articles was restricted to three scientific databases (ScienceDirect, PubMed, and Scopus), which could have excluded relevant research published in other sources. Furthermore, the review focused on studies published between 2014 and 2024, which, while allowing for the analysis of recent trends, might not capture the full historical development of the application of CNS in higher education. Another limitation lies in the heterogeneity of the studies analyzed, since they use different methodological approaches and metrics to evaluate the effectiveness of CNS methods, which makes direct comparison of results difficult.

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