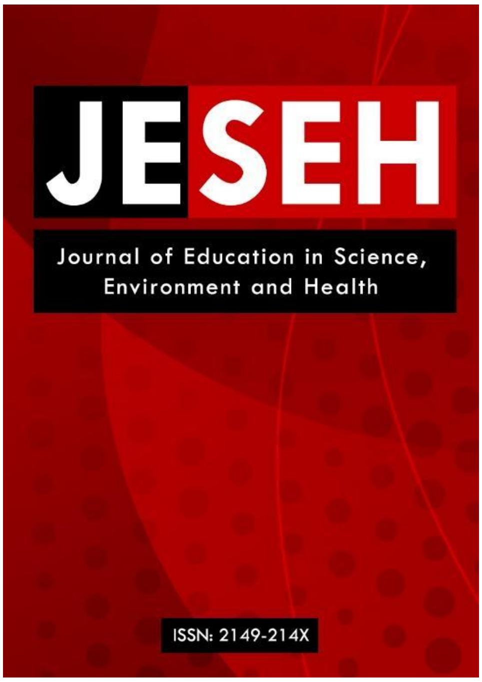

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Investigating Students' Cognitive Processes in Learning Environments: A Scoping Review from a STEM Perspective

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Abstract

This study aims to systematically review the use of portable EEG technologies in learning environments for measuring and monitoring students' attention levels. In this context, peer-reviewed studies published between 2021 and 2025 were analyzed in terms of educational levels, research purposes, findings, advantages, and limitations. The review was conducted in accordance with the PRISMA-ScR framework, and 16 studies were included. The findings indicate that the majority of studies were conducted at the university level, while a limited number were conducted at other educational levels. It was determined that portable EEG technologies are mainly used to monitor attention levels, predict academic performance, and provide feedback through developed systems. In addition, EEG data provided important insights into cognitive load, learning performance, and social interactions, such as inter-brain synchronization. Overall, portable EEG technologies have significant potential to improve STEM learning environments and enable real-time, objective evaluation of cognitive processes. However, limitations such as data quality, movement restrictions, and challenges in long-term applications still persist. For future research, it is recommended that EEG data be integrated with learning analytics and that its use be expanded across different educational levels and stages of STEM education.

Introduction

Education is an activity that involves attention-demanding processes as well as other higher-order cognitive tasks related to learning and understanding (Orovas, Sapounidis, Volioti &Keramopoulos, 2024). One of the most important characteristics of the human brain in the learning process is cognition, which encompasses attention and information retention. Students' attention spans and their situational engagement during learning have consistently been the subject of research (Aggarwal, Lamba, Verma, Khuttan & Gautam 2021). Attention is very important for positive classroom behavior and emotional well-being. In the early school years, attention skills have significant effects on children's future academic success (Savina, 2026). Quantitatively measuring attention in the learning process is highly important, yet equally difficult. Traditional methods such as surveys and observations are subjective and limited in terms of accuracy (Rehman, Shi, Ullah, Wang & Ma, 2025). In previous studies, cognitive processes have generally been examined indirectly through observation, self-report, and performance-based methods. However, these approaches remain superficial in helping us understand cognitive processes. For example, students may appear disengaged while actively thinking, or they may give the impression of being attentive despite not showing meaningful engagement, or they may give the impression of being attentive even when not showing meaningful engagement. Therefore, such methods cannot precisely determine when a student's cognitive processes actually occur (Yang, Neville, and Riordáin, 2025; D'Mello, Dieterle & Duckworth, 2017). For instance, students may appear to be reading with deep attention, whereas the process they are engaging in may actually be mindless reading (Reichle, Reineberg & Schooler, 2010). Modern neurotechnologies offer new ways to improve and transform learning environments. The most important advantage of using these technologies is the enhancement of students' cognitive functions and the evaluation and future improvement of the educational process (Verbitskaya & Gaev, 2024). Cognitive neuroscience research is generally conducted in controlled laboratory settings. Therefore, its contributions to understanding learning in real-world environments are limited. However, in recent years, portable and wearable devices have become more accessible for classroom-based research. As a complement to existing educational research methods, these new technologies can provide insights into learning processes that are not reflected in classroom observations or learners' self-reports (Davidesco, Matuk, Bevilacqua & Poeppel, 2021).

The use of electroencephalogram (EEG) and other brain imaging techniques in education has paved the way for the field of neuroeducation. The primary goal of this field is to gain insight into the brain mechanisms involved in learning and to support the evaluation and improvement of educational methodologies based on students' brain responses (Orovas, Sapounidis, Volioti & Keramopoulos, 2024). EEG stands out not only for its ability to record the brain's electrical activity with high temporal resolution but also for its capacity to detect changes in this activity at the millisecond level. This feature makes EEG an ideal tool for examining dynamic brain processes such as learning (Yang, Neville & Riordáin, 2025). Portable EEG technologies can complement other classroom-based research methods and provide insights into cognitive processes (Davidesco, Matuk, Bevilacqua & Poeppel, 2021). Thanks to their portability, brain synchronization can be assessed within small groups or entire classrooms. This approach makes their interactions in learning environments visible, thereby enabling the examination of their effects on learning processes. (Dikker, Wan, Davidesco, Kaggen, Oostrik, McClintock, Rowland, Michalareas, Bavel, Ding & Poeppel, 2017). Portable EEG enables monitoring and enhancement of attention in natural educational settings. Future studies are needed to verify the long-term stability of portable EEG devices and to uncover the brain mechanisms underlying natural learning interactions (Wang, Zang & Johnstone, 2025).

STEM is a broad term that encompasses interdisciplinary skills integrating science, technology, engineering, and mathematics (Flegr, Kuhn & Scheiter, 2023). To understand the neural mechanisms underlying interest and learning in Science, Technology, Engineering, and Mathematics (STEM), it is important for fostering creativity and problem-solving skills, which are key drivers of technological and educational advancement. Traditional methods for measuring interest in STEM are often limited by bias, underscoring the need for more objective approaches (Candela-Leal, Alanis-Espinosa, Murrieta-Gonzalez et al., 2025). Cognitive neuroscience research is typically conducted in controlled laboratory settings that bear little resemblance to science, technology, engineering, and mathematics (STEM) classrooms. Recent advances in portable EEG technology allow researchers to collect brain data from students in real classroom environments (Davidesco, 2020).

This study aims to systematically examine the use of portable EEG technology in learning environments and to address the gap in the literature by evaluating existing applications and methodological approaches from a STEM perspective. Although previous studies have demonstrated that portable EEG has been used for various purposes in educational settings, the existing body of research varies in terms of educational levels, research purposes, and key findings. Therefore, there is a need for a comprehensive synthesis that identifies the overall trends in this field. This review aims to systematically map the existing literature, identify current research trends and research gaps, and provide directions for future research. In line with these objectives, the present review was conducted based on the following research questions:

1. At which educational levels have studies involving portable EEG technology in learning environments been conducted?
2. How are the purposes of using portable EEG technology to measure students' attention levels addressed in the literature?
3. What kinds of results do studies on the use of portable EEG technologies in learning environments reveal regarding the measurement and monitoring of students' attention processes?
4. What are the cognitive findings related to the use of mobile EEG technology across different educational levels?

Method

This study is a systematic review aimed at examining research conducted in learning environments using portable devices.

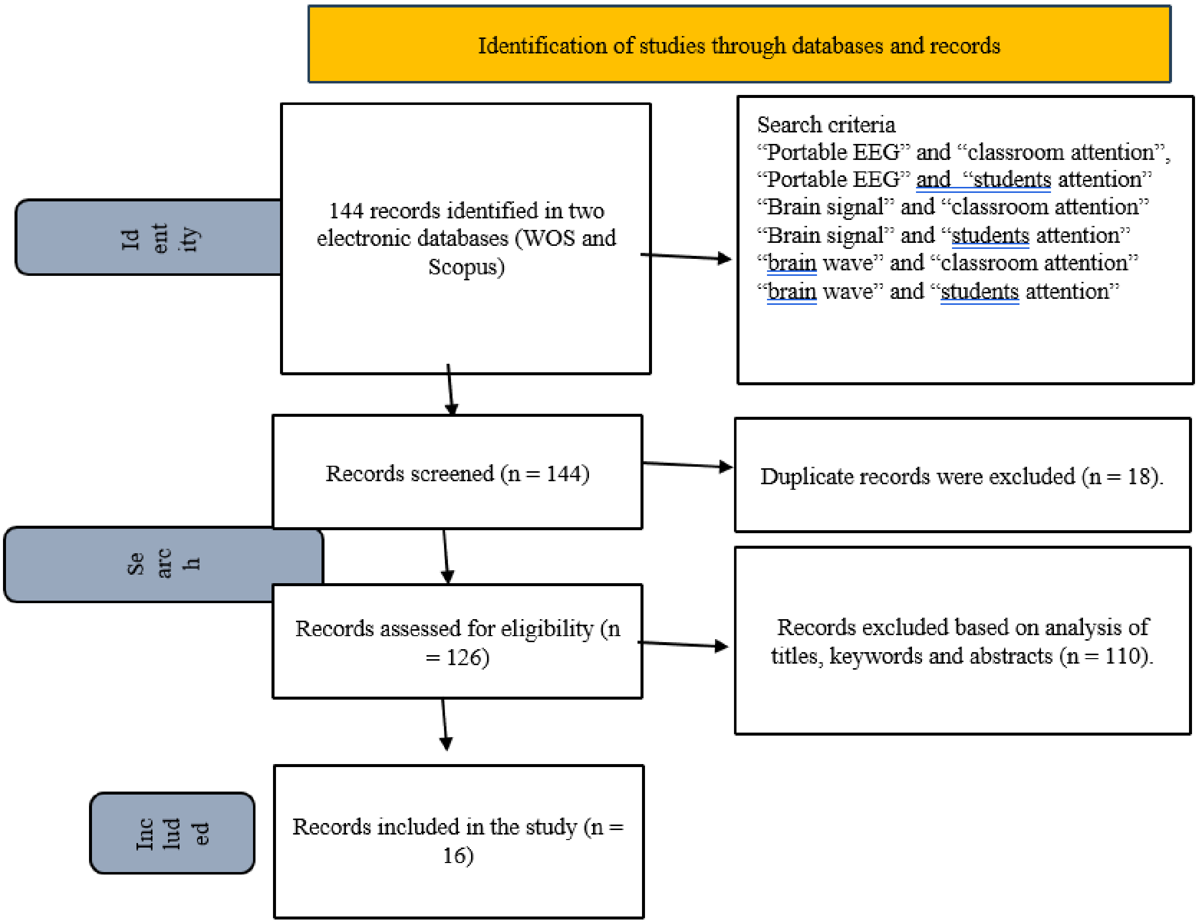
Literature Review Approach

In order to address the research questions, a scoping review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al., 2018). This study focused on peer-reviewed literature published between 2021 and 2025. This time frame was selected to reflect the use of portable EEG technologies in learning environments over the past five years. The literature search was conducted using the Scopus and Web of Science (WoS) databases. The selection of the databases was based on their broad multidisciplinary coverage across education, neuroscience, engineering, and computer science, as well as their ability to reflect the interdisciplinary nature of research on the use of portable EEG in educational settings. In addition, the search strategy was designed to balance comprehensiveness with methodological feasibility. Limiting the search to Scopus and Web of Science enabled the implementation of a predefined, transparent, and reproducible search strategy, while ensuring a systematic screening process aligned with the objectives and scope of this scoping review. A consistent set of search terms was used during the search. The search terms were applied in English. The advanced search in the databases was conducted as follows:

"Portable EEG" AND "classroom attention"
"Portable EEG" AND "students' attention"
"Brain signal" AND "classroom attention"
"Brain signal" AND "students' attention"
"Brain wave" AND "classroom attention"
"Brain wave" AND "students' attention"

The Boolean operator "AND" was used during the search process to reach the targeted articles. In terms of inclusion criteria, this review covers peer-reviewed journal articles published between 2021 and 2025 that portable EEG technologies in learning environments. In this study, research conducted in educational contexts that used EEG was included. Studies involving non-portable EEG technologies, those conducted outside learning environments, clinically oriented studies, review-type studies, and studies without full-text access were excluded. The studies obtained through the literature review were subjected to a screening process. First, 144 articles were identified. Duplicate studies were removed. A total of 126 articles remained. Finally, titles, abstracts, and keywords were analyzed, and studies outside the research scope were excluded. As a result, the final set of studies to be included in the review (n = 16) was determined. This scoping review was conducted in accordance with the PRISMA-ScR guidelines. These stages are presented in Table 1.

Table 1. Articles reviewed in line with the research objective



Results

Research Question 1: At which educational levels have studies involving the use of portable EEG technology in learning environments been conducted?

The majority of the studies included in the review were conducted at the university level. Studies at the preschool, primary, and secondary school levels are limited in number. These studies are presented in Table 2.

Table 2. Descriptive characteristics of the studies included in the review

Order	Author(s) and year	Article title	Participants
1	Aggarwal, Lamba, Verma, Khuttan & Guatam, (2021)	A preliminary investigation for assessing attention levels for Massive Open Online Courses learning environment using EEG signals: An experimental study	University student
2	Shaw, Patra, Pradhan & Mishra (2023)	Attention Classification and Lecture Video Recommendation Based on Captured EEG Signal in Flipped Learning Pedagogy	44 Students (17-20 Age)
3	Mutlu-Bayraktar, Özel, Altındiş & Yılmaz (2022)	Split-attention effects in multimedia learning environments: eye-tracking and EEG analysis	44 University student
4	Zheng, Ma, Yue & Yang (2023)	Effects of different types of cues and self-explanation prompts in instructional videos on deep learning: evidence from multiple data analyses	72 University student
5	Shaw & Patra (2022)	Classifying students based on cognitive state in flipped learning pedagogy	84 University student
6	Hsu & Chen (2021)	An EEG Study on Students' Learning in Practical and Theory- Based Hospitality Courses	33 University student
7	Lin, Tang, Ma, Liu & Ding (2023)	The impact of media diversity and cognitive style on learning experience in programming video lecture:A brainwave analysis	15 University student
8	Cardoso & Zaro (2023)	Monitoring Learning in Nursing using the Electroencephalogram and Intrinsic Motivation Inventory–IMI	17 University student
9	Shaw, Mohanty, Patra & Pradhan (2023)	1D Multi-Point Local Ternary Pattern: A Novel Feature Extraction Method for Analyzing Cognitive Engagement of students in Flipped Learning Pedagogy	44 University student
10	Chen, Xu & Zhang (2024)	Inter-brain coupling analysis reveals learning-related attention of primary school students	35 Primary school student
11	Juárez-Varón, Juárez-Varón Mengual-Recuerda & Andres, (2024)	A Neurotechnological Study to Quantify Differences in Brain Activity Using Game-Based Learning: Gamification vs. Traditional Teaching	20 University student
12	Grammer, Xu & Lenartowicz (2021)	Effects of context on the neural correlates of attention in a college classroom	23 University student
13	Xie, Dong, Yang, Luo, Ren, Zhang, He, Jia, Yang, Jiang, Gao, Chen (2025)	CNN-Transformer network for student learning effect prediction using EEG signals based on spatio-temporal feature fusion	16 University student
14	Guo, Zhu, Wu, Bao & Liu (2022)	Emotional Activity Is Negatively Associated With Cognitive Load in Multimedia Learning: A Case Study With EEG Signals	42 University student
15	Xu, Torgrimson, Torres, Lenartowicz & Grammer (2022)	EEG Data Quality in Real-World Settings: Examining Neural Correlates of Attention in School-Aged Children	46 Kindergarten to 4th-grade students
16	Fuentes-Martínez, Romero, Lopez-Gordo Minguillon & Rodríguez-Álvarez (2023)	Low-Cost EEG Multi-Subject Recording Platform for the Assessment of Students' Attention and the Estimation of Academic Performance in Secondary School	34 Secondery school

Research Question 2: How are the purposes of using portable EEG technology to measure students' attention levels addressed in the literature in learning environments?

When the aims of the reviewed studies were analyzed, it was found that although portable EEG technologies are; primarily used to measure attention, they were also used for other purposes. The identified purposes were categorized into groups. The aims were organized under seven categories. Since a single study may have multiple purposes, it may appear in more than one category. The scope and purposes of using portable EEG technology to measure attention levels in learning environments in these studies are presented in Table 3.

Table 3. Categories of the studies included in the review

Scope	Detail	Author–Year
To directly determine and assess students' attention levels	To assess students' attention levels in massive open online course environments using brain signals.	Aggarwal, Lamba et al. (2021)
	To detect students' attention levels during class by applying classification techniques to EEG brain wave data.	Shaw, Patra, Pradhan & Mishra (2023)
	To objectively determine students' attention levels while watching pre-recorded lecture videos in flipped learning environments.	Shaw, Mohanty, Patra & Pradhan (2023)
	To examine how different instructional contexts in the classroom (student-initiated vs. teacher-initiated activities) affect student attention using portable EEG measurements, and to reveal attention differences that behavioral observations and self-reports cannot capture.	Grammer, Xu & Lenartowicz, (2021)
	To monitor students' attention levels in a classroom environment.	Xu, Torgrimson, Torres, Lenartowicz & Grammer (2022)
	To assess students' attention and address issues in online education, such as students turning off their cameras and microphones.	Fuentes-Martinez, Romero et al. (2023)
To compare an implemented intervention with traditional instruction	To compare the attention levels of learners in massive open online course (MOOC) environments with those in traditional classroom instruction	Aggarwal, Lamba et al. (2021)
	To investigate the neural activity exhibited by students during practical and theoretical classes	Hsu & Chen (2021)
	To comparatively examine brain activity during gamified and traditional instruction in classroom settings.	Juárez-Varón, Juárez-Varón Mengual-Recuerda & Andres (2024)
	To examine how different instructional contexts in the classroom (student-initiated vs. teacher-initiated activities) affect student attention using portable EEG measurements, and to reveal attention differences that cannot be captured through behavioral observations and self-reports.	Grammer, Xu & Lenartowicz, (2021)
To observe the effects of divided attention in learning environments	To examine split attention in multimedia learning environments.	(Mutlu-Bayraktar, Özel, Altındiş & Yılmaz (2022)
To develop a new system to provide feedback on students' attention levels and to assess them	A recommendation system called FlipRec is developed to re-suggest videos on which students showed inattention.	Shaw, Patra, Pradhan & Mishra (2023)
	A prototype (model) is developed to monitor students in flipped learning by passively recording their individual brain waves as they engage with instructional videos.	Shaw & Patra (2022)
	To evaluate the learning process of undergraduate nursing students who voluntarily participated in the study using a pilot virtual environment (VM).	Cardoso & Zaro (2023)
	to determine students' attention levels while watching pre-recorded lecture videos in flipped learning environments and to develop an effective EEG-based analysis and classification method for this purpose	Shaw, Mohanty, Patra & Pradhan (2023)
	To develop a new method based on inter-brain attention coupling rather than individual attention measures in order to more accurately determine learning-related attention in primary school students, and to test the	Chen, Xu & Zhang (2024)

	predictive power of this method for academic achievement	
	To propose a hybrid CNN–Transformer (HCT) model that enables the discrimination of high- and medium-level learning outcomes from EEG signals recorded during learning	Xie, Dong, Yang, Luo, Ren, Zhang, He, Jia, Yang, Jiang, Gao & Chen (2025)
	To develop a new low-cost EEG-based platform to assess students' attention and predict their academic performance in online education	Fuentes-Martinez, Romero et al. (2023)
to examine the effects of an implemented program/system on brain waves	To examine the combined effects of media diversity and cognitive style on university students' sustained attention, learning engagement, cognitive load, and learning outcomes from the perspective of EEG signals	Lin, Tang, Ma, Liu & Ding (2023)
	To investigate the relationship between emotional activity and cognitive load using EEG signals from the perspective of emotion dynamics during multimedia learning	Guo, Zhu, Wu, Bao & Liu, (2022)
	EEG data are used to determine participants' attention levels and learning engagement while watching instructional videos.	Zheng, Ma, Yue & Yang (2023)
to evaluate the collectability and quality of EEG data in different environments	To examine the feasibility of mobile EEG across different ecological contexts by collecting EEG data both in a field laboratory under a controlled one-on-one interaction setting and during real classroom lessons conducted in the same school	Xu, Torgrimson, Torres, Lenartowicz & Grammer (2022)
to relate attention levels to academic achievement	To develop a new low-cost EEG-based platform to assess students' attention and predict their academic performance in online education by addressing issues such as students' ability to turn off cameras and microphones to protect their privacy.	Fuentes-Martinez, Romero et al. (2023)

As shown in Table 3, the findings indicate that the purposes of the studies are mostly grouped under the categories of "directly determining and evaluating students' attention levels" and "providing feedback or evaluation of students' attention levels by developing new systems." In addition, a limited number of studies were found to fall under the categories of "evaluating the collectability and quality of EEG data in different environments" (n = 1), "observing the effects of divided attention in learning environments" (n = 1), and "associating attention levels with academic achievement" (n = 1). It is observed that EEG is used in measurement and evaluation processes or in determining the effectiveness of learning environments. These findings show that EEG research primarily focuses on cognitive processes. Considering the specific purposes of the studies, it is evident that EEG technologies are also used in video lectures, flipped learning methods, and online learning environments.

Research Question 3: What kinds of results do studies on the use of portable EEG technologies in learning environments reveal regarding the measurement and monitoring of students' attention processes?

Developed Systems and Attention Analysis

In e-learning and flipped learning environments, systems designed to identify students with low attention have been shown to be effective. These systems can identify lecture videos in which students fail to maintain attention and provide appropriate content recommendations. This enables the identification of students with low attention levels and provides personalized support (Shaw, Patra, Pradhan & Mishra, 2023). It is also indicated that such systems are suitable for the real-time and objective assessment of both students' attention and their subsequent academic performance (Fuentes-Martinez, Romero et al., 2023).

Video Lecture Designs, Media Types, and Cognitive Load

In video-based learning, textual and visual cues presented to students have been found to positively affect learning (Zheng, Ma, Yue & Yang, 2023). In addition, a negative relationship has been observed between cognitive load and emotional engagement. This has been considered an important indicator in the design of video lectures. It is emphasized that learning environments should be designed to balance students' emotional engagement while reducing cognitive load and enhancing learning (Guo, Zhu, Wu, Bao & Liu, 2022). Findings based on EEG data indicate that the diversity of video types used in video lectures has significant effects on learning. The effects of different materials, such as presentations, tablet drawing, and animations, were examined; it was found that tablet drawing increased students' focus and engagement in learning compared to animation use. However, it was revealed that both animated materials and tablet drawing materials lead to a higher cognitive load compared to presentations (Lin, Tang, Ma, Liu & Ding, 2023)

Limitations and Contributions of EEG Use

Findings on EEG use indicate that this technology has certain limitations for long-term applications. It has been noted that factors such as the requirement for participants to remain still and the limited duration of applications may affect the results obtained (Zheng, Ma, Yue & Yang, 2023). At the same time, EEG provides teachers with valuable, objective feedback, thereby enhancing effectiveness in both face-to-face and online learning environments. Feedback obtained from EEG data can be appropriately interpreted by teachers and used to guide instruction. It is low-cost while still helping to predict students' academic performance (Fuentes-Martinez, Romero et al., 2023). EEG signals are a powerful tool for understanding differences in cognitive states related to classroom instruction that cannot be observed solely through behavior (Grammer, Xu & Lenartowicz, 2021). EEG signals have been found to provide objective feedback to teachers and contribute to the improvement of instructional processes in both face-to-face and online learning environments. In particular, a significant relationship between beta waves and academic performance has been identified, and it has been suggested that this relationship can guide the learning process. Additionally, even low-cost portable EEG systems have been shown to be functional in predicting students' academic performance (Fuentes-Martinez, Romero et al., 2023). EEG signals have been identified as a powerful tool for understanding students' cognitive states beyond observable behaviors (Grammer, Xu & Lenartowicz, 2021). It is stated that EEG data provides an important basis for dynamic monitoring and prediction of the learning process, while also contributing to students' self-regulation of their learning (Xie, Dong, Yang et al., 2025).

Comparison of Learning Environments

EEG-based studies suggest that students' attention levels vary across different learning environments. In particular, higher attention levels have been reported in e-learning and gamified learning environments than in traditional classroom instruction (Aggarwal, Lamba, Verma et al., 2021; Juárez-Varón, Mengual-Recuerda, and Andrés, 2024).

Research Question 4: What are the cognitive findings related to the use of mobile EEG technology across different educational levels?

EEG Data at Primary and Secondary School Levels

According to the reviewed studies, it is confirmed that monitoring attention levels in primary school students in learning environments is feasible and that EEG data can be collected from young children in natural settings, and that EEG data can be collected (Xu, Torgrimson, Torres, Lenartowicz & Grammer, 2022). In addition, no direct relationship was found between attention and academic performance among primary school students. However, a positive relationship was identified between students' academic performance and inter-brain attentional coupling with their peers in the classroom. This suggests that learning may be associated not only with individual attention but also with socio-cognitive interactions (Chen, Xu and Zhang, 2024). In studies conducted with high school students, a direct relationship was found between the beta band and academic performance. It has been demonstrated that even low-cost EEG platforms are functional and can be used to predict students' academic performance. It is stated that such systems can contribute to instructional processes by providing teachers with data-driven feedback (Fuentes-Martinez, Romero et al., 2023).

EEG Data at the University Level

Undergraduate studies indicate that attention levels differ between practical and theoretical courses, suggesting that different instructional contexts are associated with different patterns of brain activity (Hsu and Chen, 2021).

In addition, gamified activities have been found to elicit higher attention than traditional learning activities (Juárez-Varón, Mengual-Recuerda, & Andrés, 2024). Furthermore, student-initiated activities elicit higher attention than instructor-initiated activities. Overall, attention levels are reported to be higher in learning situations where students are actively engaged (Grammer, Xu, & Lenartowicz, 2021). It has also been observed that attention levels vary across learning environments. For example, in e-learning environments, attention levels tend to increase as the lesson progresses, whereas in classroom settings, initially high attention levels decrease over time (Aggarwal, Lamba, Verma et. al., 2021). At the undergraduate level, EEG-based systems have been developed to analyze EEG data collected during online learning and predict students' learning outcomes (Xie, Dong, Yang et al., 2025). Students' attention levels at the university level have been classified as attentive/inattentive (Shaw, Mohanty, Patra & Pradhan, 2023; Shaw, Patra, Pradhan & Mishra, 2023). Studies conducted with undergraduate students show that different multimedia presentation formats are associated with students' emotional engagement. In this context, a negative relationship between emotional activity and cognitive load has been identified (Guo, Zhu, Wu, Bao & Liu, 2022).

Discussion

This study aims to synthesize and evaluate research on portable EEG for measuring attention in learning environments from a STEM perspective, focusing on educational levels, research purposes, obtained results, advantages, and limitations. The analysis of the selected 16 journal articles shows that portable EEG technology in learning environments is primarily used to directly measure attention and to develop new systems.

The use of EEG technology has been predominantly among university-level students, with a limited number of studies conducted at preschool, primary, and secondary school levels. Lee, Ahn, Park, 2022, similarly, it has been reported that portable EEG is most frequently used at the university level in academic contexts, mainly in science-related fields, and is employed to measure students' attention using mobile EEG. Yang, Neville & Riordáin (2025)'s study shows that the use of portable EEG in educational environments involves students at secondary and university education levels. STEM education is structured to suit students' developmental stages at different educational levels and to enable the development of engineering design skills (Bybee, 2013; Honey, Pearson & Schweingruber, 2014). It should be emphasized that the widespread adoption of EEG-based studies across different educational levels suggests the potential of this technology to evaluate STEM learning processes in a multidimensional way.

The objectives of the examined studies were grouped under seven categories. It was determined that most objectives focus on directly examining students' attention levels and on developing new systems to provide feedback on them. Similarly, Wang, Zhang & Jonstone (2025) identified three objectives in their systematic review: evaluating the effects of learning-related factors on attention, developing algorithms and software for attention monitoring and improvement, and validating the data quality of portable EEG devices. In addition, the present study included a limited number of articles that aimed to evaluate the collectability and quality of EEG data across different environments, observe the effects of divided attention in learning environments, and examine the relationship between attention levels and academic achievement. These findings indicate that research objectives related to EEG usage are predominantly concentrated on the investigation of cognitive processes.

Recent technological advances have led to the increasing use of immersive and digital learning technologies in educational settings, highlighting the need to better understand their cognitive effects on learners (Makransky et al., 2019; Skulmowski & Xu, 2022; Khan et al., 2025). However, some perspectives suggest that such technologies may distract attention or increase mental workload. These concerns highlight the need for objective methods to assess individuals' cognitive load when using these technologies.Cognitive research can be applied across various disciplines, including learning sciences, STEM, psychology, neuroscience, and education. Attention and cognitive load indicators obtained through EEG can provide important evidence for evaluating how students' learning processes change in STEM learning environments. Based on this information, EEG-based indicators of attention and cognitive load can provide important evidence for evaluating how students' learning processes change in STEM learning environments.

Active learning requires students to direct their attention to learning activities and to carry out the learning process by establishing relationships between topics and concepts (Şahinel, 2003). The findings of studies investigating the use of portable EEG technologies in learning environments to measure and monitor students' attention processes are addressed under the following themes: developed systems, video-based lessons, limitations and advantages of EEG use, and comparisons of learning environments.

EEG-based systems have been shown to identify students with low attention, detect lessons in which students fail to maintain attention, and provide personalized support for students with low attention levels (Shaw, Patra, Pradhan, & Mishra, 2023), as well as assess students' academic achievement both in real time and at subsequent stages (Fuentes-Martinez, Romero et al., 2023).

Findings from the video lesson processes indicate that video diversity plays an important role in learning; the use of tablet drawing and animation has been shown to enhance attention compared to traditional presentations, though it also increases cognitive load (Lin, Tang, Ma, Liu & Ding, 2023). A negative relationship has been found between cognitive load and emotional engagement. It has been emphasized that learning environments should be designed to reduce cognitive load and enhance learning (Guo, Zhu, Wu, Bao & Liu, 2022). EEG technologies are effective in measuring cognitive load fluctuations and attention during learning processes (Antonenko, Paas, Grabner & van Gog, 2010). Activities that contain a large number of information elements create cognitive load. For effective learning, instructional design should be structured to reduce unnecessary cognitive load and facilitate learning (Sweller, 2011). In designed STEM activities, monitoring the process with EEG can provide feedback on situations such as the emergence of unnecessary cognitive load, thereby contributing to the redesign of activities and supporting students' learning processes.

Its low cost, the ability to provide objective feedback in both face-to-face and online educational environments, and the potential for teachers to interpret EEG data to guide instruction are among its key advantages (Fuentes-Martinez, Romero et al., 2023). EEG also helps predict students' academic performance (Fuentes-Martinez, Romero et al., 2023) and serves as a powerful tool for understanding cognitive states that cannot be observed solely through behavior (Grammer, Xu, & Lenartowicz, 2021). Furthermore, EEG enables dynamic monitoring of the learning process and supports students in monitoring and regulating their own learning (Xie, Dong, Yang et al., 2025). However, obtaining high-quality EEG recordings, inferring causality, and measuring dynamic interactions in natural learning contexts remain challenging (Davidesco, Matuk, Bevilacqua, Poeppel, & Dikker, 2021). The use of portable EEG also has limitations in long-term applications (Wang, Zhang & Jonstone, 2025). These technologies provide insights into learning processes that may not be detectable in classroom settings or accurately reflected in students' self-reports; however, further research is needed to determine their unique contributions (Davidesco, Matuk, Bevilacqua, Poeppel, & Dikker, 2021). As research in this area increases . Factors that decrease or enhance across STEM fields; it is expected that, beyond general knowledge of the learning process, students' cognitive states will be evaluated second-by-second or minute-by-minute. Factors that increase or decrease attention levels during the process will be identified individually, revealing previously overlooked findings.

According to the studies examined, it is feasible to collect EEG data from students in preschool and primary school settings and to monitor their attention levels (Xu, Torgrimson, Torres, Lenartowicz and Grammer, 2022). It has been found that students' academic performance is positively associated with attention coupling in EEG data among their peers in the classroom. This suggests that learning may be related not only to individual attention but also to social-cognitive interactions. However, no significant relationship was found between individual attention and academic performance (Chen, Xu & Zang, 2024). In studies conducted at the high school level, EEG data have been reported to be functional and useful for predicting students' academic performance. It is also stated that EEG-based systems can provide data-driven feedback to teachers, thereby contributing to instructional processes (Fuentes-Martinez, Romero et al., 2023). In learning environments, inter-brain synchronization, student engagement, and learning outcomes can provide informative results (Dikker et al., 2017; Bevilacqua et al., 2019). Social interactions have been relatively underexplored in human neuroscience, as most studies have been conducted in controlled laboratory settings with individual participants. Social interactions in STEM contexts and offer promising opportunities for interdisciplinary research. There is evidence that student engagement, memory retention, and social dynamics are reflected in similarities in brain responses between teachers and students (Davidesco, 2020).

The majority of studies conducted at the university level focus on developing EEG-based systems. It has been shown that these EEG-based systems improve students' learning performance (Kim, Chae, Kim & Im, 2023) by analyze data and predict students' learning outcomes (Xie, Dong, Yang et al., 2025), classifying their attention states, and providing feedback such as "attentive" or "inattentive" (Shaw, Mohanty, Patra & Pradhan, 2023; Shaw, Patra, Pradhan, & Mishra, 2023). Studies indicate that such feedback systems enhance learning performance (Kim, Chae, Kim & Im, 2023). Theobald et al. (2020) support calls for traditional lectures in STEM disciplines to be replaced by evidence-based, active-learning-focused lesson designs and indicate that innovations in teaching strategies can increase equality in higher education.

Conclusion

This study aims to examine the use of portable EEG technologies in learning environments focusing on educational levels, research purposes, findings, advantages, and limitations. It was determined that the majority of the reviewed studies were conducted at the university level, while a limited number were conducted at the university level. In contrast, a limited number were conducted at the preschool, primary, and high school levels. The findings indicate that portable EEG technologies are used to monitor students' attention levels, predict learning performance, and provide feedback based on attention states. These technologies have the potential to provide individualized support, guide instructional processes, and improve student performance during learning. It has been observed that the use of portable EEG provides valuable data on cognitive load, learning performance, and attention. In addition, EEG data have been shown to reflect not only individual attention processes but also inter-brain synchronization associated with social interactions. EEG data were found to be functional in predicting academic performance at the high school and university levels. At the primary school level, no direct relationship was found between attention and academic achievement; instead, the alignment of inter-brain synchronization among students was highlighted. The main advantages of these technologies include providing objective data, being low-cost, and offering real-time feedback during learning processes. However, limitations such as movement restrictions in long-term use and issues related to data quality have also been identified.

Recommendations

Overall, portable EEG technologies are considered to have significant potential in STEM education for the multidimensional evaluation of learning processes, analysis of attention and cognitive load, and improvement of instructional processes. Future research is recommended to conduct more studies across different educational levels, to examine cognitive processes in STEM activities in greater detail, to compare students' cognitive processes across different learning environments, to expand applications that provide feedback based on these processes, and to integrate EEG data with learning and attention analytics.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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