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Portable EEG for assessing attention in educational settings: A scoping review

Jian-Wei Wang [a,1], Da-Wei Zhang [a,b,*,1], Stuart J. Johnstone [c,d]

[a] Department of Psychology, Yangzhou University, Yangzhou, China
[b] Department of Psychology, Monash University Malaysia, Bandar Sunway, Malaysia
[c] School of Psychology, University of Wollongong, Wollongong, Australia
[d] Brain Behaviour Institute, University of Wollongong, Wollongong, Australia

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ABSTRACT

Background: Portable EEG provides the opportunity to capture neural correlates of attention in a more naturalistic environment. However, the field is still in its infancy, with varied research aims and methodologies. The current scoping review aims to clarify: (1) the research aims of the studies, (2) the portable EEG collection methodologies, and (3) the EEG measures of attention.
Method: The review followed the Preferred Reporting Items for Systematic Review and Meta-Analysis - Scoping Review extension. Two authors extracted data items from 45 eligible studies.
Results: Three research aims were identified in previous studies: examining the effects of learning-related factors on attention captured by portable EEG ($n = 23$), developing attention classification algorithms ($n = 7$) and software for monitoring and promoting attention ($n = 10$), and verifying the signal quality of EEG derived from portable EEG in attentional tasks ($n = 5$). The testing sites and tasks were predominantly out-of-lab controlled settings and structured learning materials. To quantify attention, 8 studies employed a theory-driven approach, e.g., using EEG measures based on prior research correlating specific spectral power with attention. In contrast, 37 studies used data-driven approaches, e.g., using spectral power as input features for machine learning models to index attention.
Discussion: Portable EEG has been a promising approach to measuring attention in educational settings. Meanwhile, there are challenges and opportunities related to the better translation of cognitive neuroscience research into practice.

1. Introduction

Attention, probably a watchword of educators everywhere, is a critical factor for inducing learning (Baddeley et al., 1984; Muzzio et al., 2009). To facilitate efficient learning, learners need to maintain an alert state, reduce distractors, and regulate themselves - these processes rely on three distinct attentional networks in the brain namely the alerting network, the orienting network, and the executive attention network (Petersen and Posner, 2012; Posner and Rothbart, 2014). Attention can be measured via self-reported methods (e.g., questionnaires), computerized tasks, (e.g., reaction time based attentional tasks) and cognitive neuroscience methods (e.g., electroencephalogram, or EEG, and functional magnetic resonance imaging, or fMRI). Compared to behavioral approaches, cognitive neuroscience approaches theoretically have advantages in revealing neural correlates of attention, particularly covert attention, without relying on observable responses (Petersen and Posner, 2012). Practically, these methods enable live tracking of attentional states (deBettencourt et al., 2015), provide a standardized way of quantifying attention (Rosenberg et al., 2016), and offer unique explanations for individual differences in attention (Williams et al., 2016).

Cognitive neuroscience research into attention has mainly been conducted in laboratories with strict experimental control, which limits its ecological validity. While strict experimental controls can assist in understanding the causal role of attention in learning (e.g. Arrington et al., 2019; Mantini et al., 2009), such studies may ignore the complex and dynamic interactions in real-world learning contexts (Bevilacqua

* Corresponding author at: Department of Psychology, Monash University Malaysia Campus, Malaysia.
E-mail address: dawei.zhang@monash.edu (D.-W. Zhang).
[1] These two authors contributed equally to this work

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et al., 2019; Dikker et al., 2017). To address this issue, the notion of "bringing the lab to the real world" has been proposed through mobile neuroimaging technology (Janssen et al., 2021).

Recently, the advent of portable EEG devices has brought opportunities for assessing attention in a more natural context. EEG directly measures large-scale and synchronized electrical activity primarily from cortical neuron populations with high temporal resolution but limited by signal attenuation and the constraints of electrode sensitivity (Cohen, 2017). Traditional EEG measures have provided a solid foundation for assessing attention. In the frequency domain, increases in theta (~3–8 Hz) and beta (~13–30 Hz) activity, along with decreases in alpha activity (~8–12 Hz), are often associated with heightened attentional engagement and control (for detailed discussion, please see Engel and Fries, 2010; Fiebelkorn and Kastner, 2019; Nobre and Van Ede, 2018). In the time domain, ERP components emerging around 200–300 ms (typically reflecting the N2) and those occurring around 300–500 ms (typically reflecting the P300) have been linked to selective attention and decision-related processing in laboratory settings (for detailed discussion, please see Luck et al., 2000). Portable EEG has recently been made possible due to technological advancements in hardware and software (for details please see Lau-Zhu et al., 2019). Portable EEG, also known as "mobile EEG" or "wireless EEG," is a broad concept that, as defined by Bateson et al. (2017), encompasses various systems differing in device mobility (ranging from off-body setups with cabling to head-mounted wireless configurations), participant mobility (from stationary to unconstrained movement), and system specifications (e.g., such as the number of channels and data quality). Portable EEG has the comparable signal quality to traditional EEG systems devices (i.e., Edwards and Trujillo, 2021; Kam et al., 2019; McWilliams et al., 2021; Radüntz, 2018) but also offers the benefits of wireless transmission (i.e., via Bluetooth or Wifi), easy installation, and low cost. However, portable EEG systems face challenges, for example, ensuring robust data quality in naturalistic settings and limited scalp coverage, which can affect data quality and reliability (for comprehensive reviews, please see Lau-Zhu et al., 2019; Biondi et al., 2022; Niso et al., 2023). Despite these limitations, the benefits of portable EEG make it a candidate tool for capturing the dynamics of attention in naturalistic educational settings. Recent studies have used portable EEG in educational settings to examine the effects of different presentation forms of learning material (Chen and Wu, 2015; Grammer et al., 2021), the impact of school activities (Dikker et al., 2020), and interactions between students and teachers (Bevilacqua et al., 2019). However, it can be noted that the field is still in its infancy, with varied research aims and methodologies.

As a knowledge synthesis form, a scoping review is suitable for providing methodological insights to bridge the methodologic knowledge gap (Colquhoun et al., 2014; Munn et al., 2018). Therefore, the current study conducted a scoping review on the application of portable EEG for assessing attention in educational settings. Specifically, the current scoping review aimed to clarify the following: (1) the primary research aims for using portable EEG in educational settings, which helps uncover the motivations behind studying attention in learning environments; (2) the data collection methodologies employed, including participant sampling, testing environments, and device setup, to understand how EEG data is gathered in educational settings; and (3)

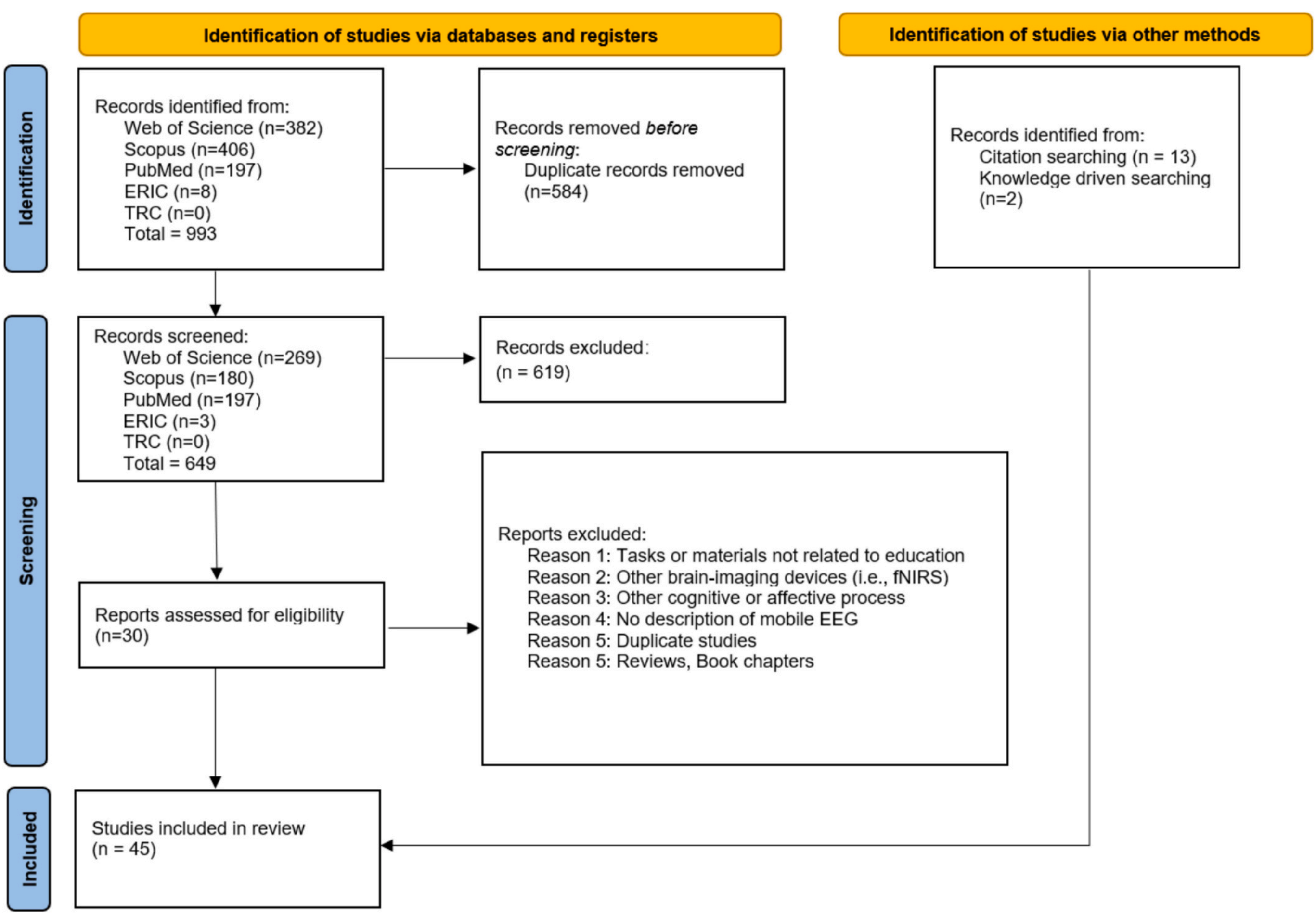

Fig. 1. Flowchart The retrieval and screening process. Our search strategy included the following keywords: ("attention" OR "concentrat*" OR "engage*") AND (("portable" OR "mobile" OR "wireless" OR "wearable" OR "Bluetooth" OR "smartphone" OR "rapid respond" OR "consumer" OR "ear") AND ("EEG" OR "electroencephalogram" OR "electroencephalography" OR "brain waves")) AND ("learn*" OR "student*" OR "instruct*" OR "classroom" OR "educat*").

the specific EEG measures used to quantify attention, identifying the consistency and variability in EEG metrics applied across studies. Together, these questions provide a comprehensive overview of current practices and insights to guide future applications of portable EEG in education.

2. Methods

This scoping review adhered to the Preferred Reporting Items for Systematic Review and Meta-Analysis Scoping Review extension (PRISMA-ScR) (Tricco et al., 2018). The procedure is illustrated in Fig. 1.

2.1. Eligibility criteria

The inclusion criteria for this review included studies that used portable EEG devices in educational settings. In this review, portable EEG devices refer to systems with a device mobility rating greater than 1 on the Categorisation of Mobile EEG scheme (Bateson et al., 2017), a threshold that ensures inclusion of EEG systems sufficiently mobile to support realistic interactions within educational contexts. These portable systems offer unique advantages for unobtrusive monitoring in educational settings due to their flexible designs (Janssen et al., 2021). Although not listed in the Categorisation of Mobile EEG scheme, ear EEG was also included in this review as it provides an unobtrusive approach to monitoring brain activity, using flex-printed electrode arrays positioned in or around the ear to enable long-term recording (Bleichner and Debener, 2017; Kaongoen et al., 2023). Educational settings were defined as environments facilitating naturalistic or semi-naturalistic learning activities, such as classrooms or online platforms.

This review included only studies that explicitly focused on capturing attention as a primary measure. For studies assessing multiple cognitive functions, only attention-related content was extracted.

Further criteria specified that studies (3) were peer-reviewed and (4) available in English.

2.2. Information search

2.2.1. Databases

Information was retrieved from five databases: Web of Science, Scopus, PubMed, Education Resources Information Centre (ERIC), and Teacher Reference Center (TRC). Web of Science and Scopus were selected for their multidisciplinary coverage, while the biomedical database PubMed was searched to include groups with special educational needs (e.g., ADHD children, visually impaired people). ERIC and TRC were chosen due to their high relevance to education. Given the interdisciplinary complexity of our topic, we supplemented our primary database search with systematic backward and forward citation tracking, as well as knowledge-driven searching. Backward citation tracking reviewed references of included studies to capture foundational research, while forward tracking identified recent studies citing these articles. Knowledge-driven searching identified influential or emerging works recognized as relevant within the field. Studies identified from the supplementary searching were evaluated using the same inclusion and exclusion criteria as those from the primary search.

2.2.2. Search strategy

This review focused on studies published from January 2010 to September 2023. Our search strategy included the following keywords:

(attention OR concentrat* OR engage*) AND (portable OR mobile OR wireless OR wearable OR Bluetooth OR smartphone OR "rapid respond" OR consumer OR ear) AND (EEG OR electroencephalogram OR electroencephalography or "brain waves") AND (learn* OR student* OR instruct* OR classroom OR educat*)

2.2.3. Information selection

The selection process is presented in Fig. 1. Duplicate documents were removed in Endnote, followed by manual screening based on titles and abstracts. Full-text reading was then conducted to check the suitability. Any disagreements on eligibility were resolved through a structured discussion process: the first author conducted an initial assessment of all studies, three research assistants independently assessed each study, and in cases of discrepancy, the corresponding author mediated to reach a final decision. Ultimately, 45 studies met the eligibility criteria.

2.3. Data extraction

Data items were listed by two authors beforehand and were modified after screening five full-text studies. Finally, data in each eligible study was extracted regarding: (1) Reference source: author, year of publication, and journal or conference published, (2) Research aim: the research topics of the studies involved in this review, (3) Participants sampling: educational stage and sample size, (4) Testing sites: the place for recording EEG, (5) Recording duration: the duration of EEG recording, (6) Material and tasks, (7) EEG measures: the EEG indicators for quantifying attention, and (8) Portable EEG device: the portable EEG device used in the research.

3. Results

The data items extracted from each eligible study are listed in Table 1.

3.1. Question 1: what were the research aims of applying portable EEG in educational settings?

Three research aims were covered in the 45 studies we reviewed:: (1) examining the effects of learning-related factors on attention, (2) algorithm and software development for attention monitoring and promotion, and (3) validating the signal quality of portable EEG devices (Fig. 2a). Each of these aims is explored in detail below.

3.1.1. Examine the effects of learning-related factors on attention

The largest proportion of studies ($n = 23$) examined the effects of learning-related factors (e.g., the presentation form of learning material or the type of interactive activities) on attention measured by portable EEG (Fig. 2a). These studies used portable EEG to index attention in response to various learning related factors. We categorized the learning-related factors into six main themes (Fig. 2b): presentation forms of learning material ($n = 8$), school activities ($n = 1$), interactive activities ($n = 6$), physical environment ($n = 3$), teaching aids ($n = 3$), and the characteristics of learners ($n = 2$). The detailed descriptions for each theme are shown below (please note that EEG measures used in each study are introduced briefly in this section. More detailed explanations are provided in Section 3.3):

- **Presentation Forms of Learning Material**: This subcategory includes studies that explored the effect of different presentation modes (i.e., online versus classroom) on attention, with a particular focus on video-based formats. In online learning, Chen and Wu (2015) compared three distinct modes of video presentation (i.e., lecture capture, voice-over presentation, and picture-in-picture), using the eSense algorithm to assess attentional changes. Ni et al. (2020) evaluated the impact of video combined with both textual and graphical elements, also utilizing the eSense metric for attention measurement. In classroom learning, Dikker et al. (2020) and Grammer et al. (2021) compared video presentations with teacher-led lectures, measuring attentional engagement with alpha and theta band power. Other studies compared various formats of learning material in different modalities. For example, Chen and Lin (2016) examined the impact of static, dynamic, and mixed text using eSense. Sezer et al. (2015) compared the effectiveness of PowerPoint

Table 1
Data items of eligible studies

Reference source: Author and Publication Year	Reference source: Publication Journal/ Conference	Research Aim	EEG collection methodology: Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	EEG Measures
(Zheng et al., 2023)	Educational technology research and development	Examine the effects of learning-related factors on attention: Interactive activities	72 college students	a learning science laboratory of a Chinese college	10 min	instructional videos about the ozone in the atmosphere with different cues and self-explanation prompts	NeuroSky's MindWave Mobile headsets	naturalistic paradigms in mobile labs	eSense
(Bitner & Le, 2022)	Journal of Information and Telecommunication	Signal quality validation of portable EEG devices	23 adults，2/3 college students	a quiet and solitary place	10 min	a pedagogical agent called 'SYNJA'	the MindWave Mobile 2	online paradigms in educational technology	delta, theta, low/high alpha, low/high beta*
(Darma Udayana et al., 2022)	2022 International Conference on Data and Software Engineering (ICoDSE)	Examine the effects of learning-related factors on attention: Physical environment	25 students aged 18–22	not mentioned	10 min	answering questions provided in an application using a smartphone and a laptop	Muse	online paradigms in educational technology	alpha, theta, beta, delta*
(Juan & Chen, 2022)	Building and Environment	Examine the effects of learning-related factors on attention: Physical environment	68 higher vocational college students	classroom	4 min	video	NeuroSky's MindWave Mobile headsets	naturalistic paradigms in naturalistic settings	eSense

Appendix Table 1 (continued)

Reference source: Author and Publication Year	Reference source: Publication Journal/ Conference	Research Aim	EEG collection methodology: Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	EEG Measures
(Shaw et al., 2022)	2022 International Conference on Advanced Learning Technologies (ICALT)	Algorithm and software development: Attention classification algorithm	44 students	lab	not mentioned	lecture video	Neurosky's EEG headset	naturalistic paradigms in mobile labs	the ratio of beta and alpha power
(Xu et al., 2022)	Mind, Brain, and Education	Signal quality validation of portable EEG devices	kindergarten to 4th-grade students (10 recruited, Mage = 7.36 yrs)	in a classroom	24 min at least	Instructional activities included a brief mindfulness session, teacher-led instruction (e.g., lecture), and student-led activities (e.g., seated work)	the EEG cap (Greentek, Wuhan, China), the SMARTING mobile EEG amplifiers (mBrainTrain, Belgrade, Serbia) with 24 Ag/AgCl saline electrodes	naturalistic paradigms in naturalistic settings	normalized alpha power*
(Aggarwal et al., 2021)	Human Behavior and Emerging Technologies	Examine the effects of learning-related factors on attention: Learning modes	12 bachelor's degree students	a relatively silent environment like a library, classroom	15–20 min	MOOC courses and classroom lectures on Machine learning	Neurosky Mindwave	online paradigms in educational technology naturalistic paradigms in naturalistic settings	alpha, beta, theta, gamma, delta, R factor (the ratio of alpha and beta power band)
(Chen et al., 2021)	2021 IEEE International Conference on Engineering, Technology & Education (TALE)	Examine the effects of learning-related factors on	18 college students	lab	12 min	classic English speeches and English poetry fragments, using	NeuralSky	online paradigms in educational technology	eSense

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Table 1 (*continued*)

Appendix Table 1 (continued)

Reference source		Research Aim	EEG collection methodology						EEG Measures
Author and Publication Year	Publication Journal/ Conference		Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	
		attention: Interactive activities Different presentation forms of learning material				the English Rubik's Cube APP with interactive dubbing			
(Grammer et al., 2021)	NPJ science of learning	Examine the effects of learning-related factors on attention: Interactive activities, Different presentation forms of learning material,	23 healthy college students recruited, 21 for analysis	a college classroom	40–60 min	video, lecture, discussion	the SMARTING mobile EEG amplifiers (mBrain-Train, Belgrade, Serbia) with 24 Ag/AgCl active scalp electrodes.	naturalistic paradigms in naturalistic settings	lower alpha, higher beta, and higher gamma power band*
(Pajk et al., 2021)	Journal of Baltic Science Education	Examine the effects of learning-related factors on attention: Learning modes	students/future farmers (n = 20) from a Biotechnical School, aged between 18 and 20	lab or self-decided place	40 min	paper-based learning materials, mobile learning platform on eco-farming	NeuralSky	online paradigms in educational technology	eSense
(Bitner et al., 2020)	12th International Conference on Computational Collective Intelligence, ICCCI 2020	Signal quality validation of portable EEG devices	27 recruited, 23 for analysis	a quiet and solitary place	10 min	a pedagogical agent called 'SYNJA'	NeuroSky's MindWave Mobile 2	online paradigms in educational technology	delta, theta, low/high alpha, low/high beta*
(Dikker et al., 2020)	Social Cognitive and Affective Neuroscience	Examine the effects of learning-related factors on attention: School activities, Different presentation forms of learning material	22 healthy high school students (age 17–18 years)	in high school classroom	15–24 min	regular biology classes (teacher-led lectures, educational videos, group discussion)	14-electrode EMOTIV EPOC wireless EEG headsets (mastoid reference locations)	naturalistic paradigms in naturalistic settings	resting state alpha activity, alpha power*
(Esquicha-Tejada et al., 2020)	6th Iberoamerican Conference of Computer Human Interaction, HCI 2020	Algorithm and system development: Attention-promoting software	a group of 104 5th and 6th grade students	in primary school	not mentioned	A memory and logic test, an attention test	Neurosky Mindwave EEG	lab paradigms in naturalistic settings	eSense
(Khng & Mane, 2020)	ADVANCED ENGINEERING INFORMATICS	Signal quality validation of portable EEG devices	45 right-handed Primary Five students recruited, 32 for analysis	in their respective schools	not mentioned	a flanker distractor interference task	the Emotiv EPOC +	lab paradigms in mobile labs	alpha, beta, delta, theta*
(Kim et al., 2020)	HortScience	Examine the effects of learning-related	30 elementary school students, aged 10 to 13 years	a room prepared for the experiment	8 min	intensive assignment with or	a wireless dry EEG device (Quick-20;	naturalistic paradigms in mobile labs	the relative theta and beta power spectrum, the

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Appendix Table 1 (continued)

Reference source		Research Aim	EEG collection methodology						EEG Measures
Author and Publication Year	Publication Journal/ Conference		Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	
		factors on attention: Physical environment		in the university		without foliage plants	Cognionics, San Diego, CA)		spectral edge frequency of 50 (SEF50), the ratio of beta and theta*
(Kumari & Deb, 2020)	Proceedings of the International Conference on Electronics and Sustainable Communication Systems (ICESC 2020)	Examine the effects of learning-related factors on attention: Teaching aids	58 undergraduate students	classroom	class hours	normal curriculum of class activity	NeuralSky Mindwave	naturalistic paradigms in naturalistic settings	eSense
(Lestari et al., 2020)	2020 6th International Conference on Science in Information Technology (ICSITech)	Algorithm and system development: Attention-motoring software	14, aged 20–30	a comfortable and quiet place	not mentioned	read a text about history and answer questions	NeuralSky Mindwave	naturalistic paradigms in mobile labs	theta, low beta, high beta
(Ni et al., 2020)	Computational and mathematical methods in medicine	Examine the effects of learning-related factors on attention: Different presentation forms of learning material	13 undergraduates and 15 postgraduates.	in a very quiet research room	30–40 min	three declarative knowledge with similar themes from the Xinhua News Agency website	NeuralSky MindWave mobile headset	naturalistic paradigms in mobile labs	eSense
(Shadiev & Huang, 2020)	Computer Assisted Language Learning	Examine the effects of learning-related factors on attention: Teaching aids	60 volunteer undergraduate students, native speakers of Russian	classroom	6 min	normal class with or without speech-enabled translation	NeuroSky MindWave	naturalistic paradigms in naturalistic settings	eSense
(Liao et al., 2019)	International Journal of Innovative Computing, Information and Control	Algorithm and system development Attention-monitoring software	15 students (male 7, female 8; average age = 19.4)	MOOC: a comfortable place traditional teaching: classroom	20 min in total (10 min for MOOC learning, 10 min for traditional teaching)	general English Proficiency Test superior course teaching video, traditional English class	NeuroSky Mindwave Mobile	online paradigms in educational technology naturalistic paradigms in naturalistic settings	eSense, the power spectrum density of low alpha, low beta wave
(Qu et al., 2019)	48th Frontiers in Education Conference, FIE 2018	Algorithm and system development: Attention classification algorithm	11 undergraduates, 2 postgraduates	not mentioned	20 min or 40 min	video, reading materials and questions on python programming and maths	Muse	not mentioned	the absolute power of alpha, beta, theta, gamma, and delta band
(Chen & Wang, 2018)	Interactive Learning Environments	Algorithm and system development Attention-promoting software	148 Grade 7 students	not mentioned	not mentioned	online English texts learning	NeuroSky's Mindset	online paradigms in educational technology	eSense

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Appendix Table 1 (continued)

Reference source		Research Aim	EEG collection methodology						EEG Measures
Author and Publication Year	Publication Journal/ Conference		Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	
(Qu et al., 2018)	Special Session on Analytics in Educational Environments	Algorithm and system development: Attention classification algorithm	14 undergraduate and graduate level college students recruited, 10 analyzed	not mentioned	80 min in total (four 20-min sessions)	GRE math problems, focus on their breath with eyes closed, GRE verbal reasoning sample test, focus on their breath with eyes open	the Muse band by Interaxon	not mentioned	the relative power of the five standard bands (alpha, beta, gamma, delta, theta) at a rate of 10 Hz
(Shimoda et al., 2018)	the 2018 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2018 ACM International Symposium on Wearable Computers	Algorithm and system development: Adaptive learning software	9 male students	not mentioned	not mentioned	lecture video	g.Nautilus manufactured by g. tec for MARTO	not mentioned	alpha, beta
(Yang et al., 2018)	Educational Technology Research and Development	Examine the effects of learning-related factors on attention: Teaching aids	60 undergraduates (VR condition 30, pencil-and-paper condition 30)	an immerse VR setting, undefied room with tables and chairs	5 min	VR drawing , pencil-and-paper drawing	NeuroSky MindWave	naturalistic paradigms in naturalistic settings	eSense
(Wang, 2017)	World Transactions on Engineering and Technology Education	Examine the effects of learning-related factors on attention: Different presentation forms of learning material	23 elementary school children (13 boys, 10 girls, aged 9–12)	not mentioned	not mentioned	picture books of different artistic styles, emotional themes, colors and design elements	NeuroSky Mindwave	not mentioned	eSense
(Chen et al., 2017)	British Journal of Educational Technology	Algorithm and system development: Attention-monitoring software	10 healthy graduate students (5 males, 5 females)	not mentioned	52 min in total (16 min, 10 min, 10 min, 16 min)	continuous performance test, video lectures	NeuroSky Mindwave	not mentioned	γ-approximate entropy, γ-total variation, β-approximate entropy, β-total variation, β-skewness, α-total variation and θ-energy
(Kuo et al., 2017)	Computers in Human Behavior	Algorithm and system development: Attention-promoting software	40 university students	in the computer classroom	60 min	online English listening course	NeuroSky's Mindset	online paradigms in educational technology	eSense
(Liu et al., 2017)	2017 IEEE/WIC/ACM International Conference on Web Intelligence, WI 2017	Algorithm and system development: Attention	11 recruited, 9 analyzed	a quiet room	not mentioned	reading, question answering, mind wandering	Muse	naturalistic paradigms in mobile labs	the average relative power for alpha, beta, theta, gamma, delta frequency band

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Appendix Table 1 (continued)

Reference source		Research Aim	EEG collection methodology						EEG Measures
Author and Publication Year	Publication Journal/ Conference		Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	
		classification algorithm							
(Sadudeemeechaithaweechoke et al., 2017)	2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)	Signal quality validation of portable EEG devices	eight volunteers, aged between 23 and 45 years old	a separated room	not mentioned	the real-time arithmetic recognition task named SpeedMath, developed by NeuroSky Inc.	NeuroSky's Mindwave Mobile	naturalistic paradigms in mobile labs	alpha, beta
(Sezer et al., 2017)	International Journal of Instruction	Examine the effects of learning-related factors on attention: Interactive activities	21 freshmen,14 for analysis	a college classroom	40 mins	lecture in the classroom	NeuroSky's Mindset	naturalistic paradigms in naturalistic settings	eSense metric
(Sun & Yeh, 2017)	Computers & Education	Algorithm and system development: Attention-promoting software	80 university students	a quiet and solitary room	18–33 min (3 min baseline)	anti-phishing instructional materials reading	NeuroSky's Mindset	naturalistic paradigms in mobile labs	eSense
(Wei & Ma, 2016)	Reading & Writing Quarterly	Examine the effects of learning-related factors on attention: Characteristics of learners, Different presentation forms of learning material	conventional picture books: 54 participants in total (24 elementary school students, 30 college and graduate students) multimedia picture books: another 24 elementary school students	not mentioned	conventional picture books: children, 3 min and 23 s on average; adults: 6 min and 3 s on average; multimedia picture books: 4 min and 40s	conventional and multimedia picture books	Neurosky MindBand	not mentioned	eSense
(Chen & Lin, 2016)	Interactive Learning Environments	Examine the effects of learning-related factors on attention: Different presentation forms of learning material	20 graduate students	in mobile environment: sitting, standing, walking	not mentioned	articles reading	NeuroSky's Mindset	naturalistic paradigms in mobile labs	eSense
(Lai et al., 2016)	International review of research in open and distributed learning	Examine the effects of learning-related factors on attention: Interactive activities	42 vocational high school students	not mentioned	50 min	a general online course in vocational high school	NeuroSky Mindwave	online paradigms in educational technology	eSense

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Appendix Table 1 (continued)

Reference source		Research Aim	EEG collection methodology						EEG Measures
Author and Publication Year	Publication Journal/ Conference		Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	
(Ma & Wei, 2016)	Interactive Learning Environments	Examine the effects of learning-related factors on attention: Different presentation forms of learning material, Characteristics of learners	48 children aged 8–9 years in Grade 3 and 48 children aged 11–12 years in Grade 6 in an elementary school	in a space without external interference.	not mentioned	conventional books, pop-up books, talking books and e-books	The NeuroSky MindBand	naturalistic paradigms in mobile labs	eSense
(Zhong et al., 2016)	2016 2nd IEEE International Conference on Computer and Communications	Algorithm and system development: Attention classification algorithm	20 undergraduates	classroom	40 min	lecture video, magazine reading, Arithmetic addition	NeuroSky MindWave	naturalistic paradigms in naturalistic settings	eSense
(Chen & Wu, 2015)	Computers & Education	Examine the effects of learning-related factors on attention: Different presentation forms of learning material	37 undergraduate students	in a controlled observation room	45 min	videos presented in three types (lecture capture format, voice-over presentation type, picture-in-picture method)	NeuroSky Mindset	online paradigms in educational technology	eSense
(Sezer et al., 2015)	Turkish Online Journal of Educational Technology	Examine the effects of learning-related factors on attention: Different presentation forms of learning material	21(17) first-year students and 21(14) second-year college students	classroom	2 h	teaching materials used by the teacher before presented using PPT, digital maps	Neurosky Mindwave	naturalistic paradigms in naturalistic settings	eSense
(Chen & Huang, 2014)	British Journal of Educational Technology	Algorithm and software development: Attention-promoting software	126 Grade 7 students from a junior high school	not mentioned	30 min	online annotated English texts reading with or without ASRLM support	NeuroSky's Mindset	online paradigms in educational technology	eSense
(Lin et al., 2014)	Computer Methods and Programs in Biomedicine	Algorithm and software development: Attention-promoting software	five male volunteers aged 24 to 30 years	not mentioned	30 min	reading e-books	The MindSet wireless Bluetooth® headset	online paradigms in educational technology	alpha, beta
(Sun, 2014)	Computers & Education	Examine the effects of learning-related factors on	32 college students	classroom	a class session	courses with in-class polling via clickers or mobile phones	NeuroSky Mindeset EEG	naturalistic paradigms in naturalistic settings	eSense

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Appendix Table 1 (continued)

Reference source		Research Aim	EEG collection methodology						EEG Measures
Author and Publication Year	Publication Journal/ Conference		Participant Sampling	Testing Site	EEG Recording Duration	Material and Tasks	Portable EEG Device	Research Paradigm	
		attention: Interactive activities							
(C.-C. Wang & Hsu, 2014)	Information & Management	Examine the effects of learning-related factors on attention: Characteristics of learners	20 college undergraduates or graduate students	a solitary room without interruption	almost 30 min	online lessons of computer-based instruction	NeuroSky Mindeset EEG	online paradigms in educational technology	eSense
(Liu et al., 2013)	Sensors (Basel, Switzerland)	Algorithm and software development: Attention classification algorithm	24 subjects aged between 22 and 27 ages	A controlled environment designed for the experiment	not mentioned	standard English class listening material	NeuroSky Mindset	naturalistic paradigms in mobile labs	alpha, beta, theta, gamma, delta, and the ratio of the energy level of alpha and beta
(Rebolledo-Méndez et al., 2010)	Proceedings of the Twenty-Third International Florida Artificial Intelligence Research Society Conference (FLAIRS 2010)	Algorithm and software development: Attention classification algorithm	40 fist-year undergraduate students (12 female)	not mentioned	an average of 9.48 min	algorithm problems in a virtual world	NeuroSky's ThinkGear	not mentioned	beta

[*] Theory-based approaches to selecting EEG measures of attention.

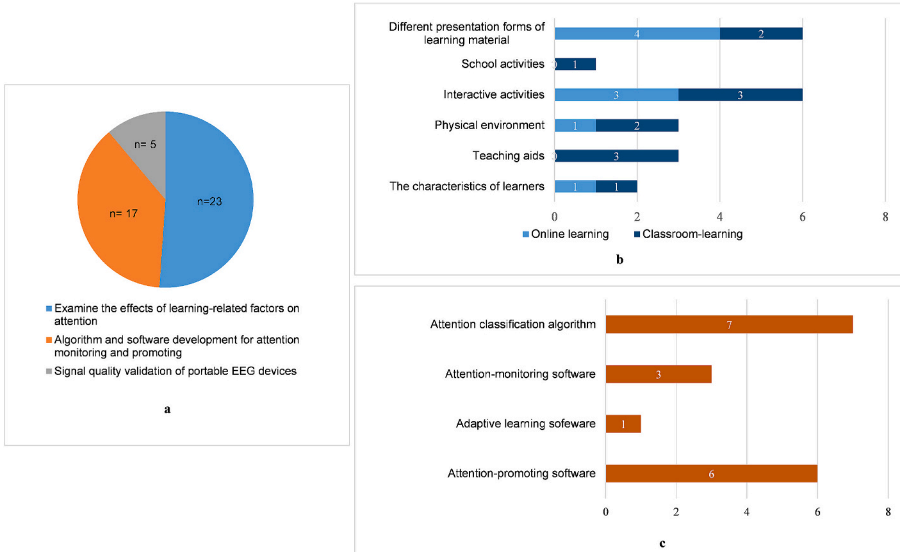

Fig. 2. The research aims of applying portable EEG to capture neural correlates of attention in educational settings **a**, the proportion of studies classified by the three research aims. **b**, the number of studies on each learning-related factor as well as classified by online learning or classroom learning. Studies with multiple research aims were classified by their main aim. Three studies conducted in both online and classroom learning were not shown. **c**, the number of studies on developing algorithms and each type of software.

slides versus digital maps, capturing attention with eSense. Studies on picture books evaluated themes and content using the eSense metric (C.-H. Wang, 2017; Ma and Wei, 2016). Additional comparisons of learning modes included studies by Aggarwal et al. (2021), which used alpha, beta, theta, gamma, and delta power, and Pajk et al. (2021), who also used eSense to assess attention in mobile versus traditional learning contexts.

- **School Activities**: This factor focuses on time-of-day influences. Dikker et al. (2020) measured attention at different times of the day using alpha power, observing how attentional states fluctuated in regular classroom settings.
- **Interactive Activities**: Several studies investigated whether attention could be enhanced through interactive activities. Grammer et al. (2021) used lower alpha, higher beta, and gamma power to measure attention during student-initiated activities, while others, such as Sezer et al. (2017) and Sun (2014), relied on eSense to assess attentional effects of classroom polling and real-time feedback in online learning (Chen et al., 2021; Lai et al., 2016; Zheng et al., 2023).
- **Physical Environment**: This theme includes studies that examined the impact of environmental factors on attention. Darma Udayana et al. (2022) used alpha, theta, beta, and delta bands to measure attention in different screen size conditions, while Juan and Chen (2022) and Kim et al. (2020) used the eSense algorithm to capture attentional variations in classrooms with diverse environmental settings.
- **Teaching Aids**: Portable EEG was used to examine the effectiveness of various teaching aids in classroom learning. Yang et al. (2018) assessed VR and traditional drawing methods using the eSense metric, while Shadiev and Huang (2020) and Kumari and Deb (2020) used the same metric to evaluate attention in real-time translation and mobile device-aided lectures.
- **Learner Characteristics**: Studies also explored how learner characteristics influence attention. Wei and Ma (2016) used eSense to examine the effect of age on attention during reading, and Wang and Hsu (2014) used the same metric to investigate attentional differences based on flow experience in online learning.

3.1.2. Algorithm and software development for attention monitoring and promoting

Seventeen studies aimed at developing attention classification algorithms ($n = 7$) and attention monitoring/promoting software ($n = 10$) with portable EEG (Fig. 2a and c).

Six studies attempted to identify live attention with machine learning algorithms, including a support vector machine (SVM) classifier (Liu et al., 2013; Rebolledo-Méndez et al., 2010; Zhong et al., 2016), a boosting and bagging of decision tree classifier (Qu et al., 2019), the K-means classifier (Qu et al., 2018), and a Logistic Regression Classifier and Multi-task Learning Classifier (Liu et al., 2017). Unlike the standard classification approaches mentioned above, Shaw et al. (2022) utilized an unsupervised learning approach to obtaining handcrafted EEG for capturing attention.

Several studies ($n = 10$) aimed at developing educational software. In terms of algorithms integrated into the software, half of these studies used a commercial algorithm developed by Neurosky Inc. called the eSense algorithm (Chen and Huang, 2014; Chen and Wang, 2018; Esquicha-Tejada et al., 2020; Kuo et al., 2017; Sun and Yeh, 2017). Although the exact details of the eSense algorithm are proprietary, it is understood to leverage frequency and amplitude characteristics in specific EEG bands associated with attention to generate the eSense scores (Bitner et al., 2020). By contrast, other studies used in-house algorithms to capture attention (Chen et al., 2017; Lestari et al., 2020; Liao et al., 2019; Lin et al., 2014; Shimoda et al., 2018). These algorithms were based on the above-mentioned machine learning approaches (Chen et al., 2017; Lestari et al., 2020; Lin et al., 2014) or previous findings to index attention, such as combining low alpha power with low beta power (Liao et al., 2019) and only using alpha power (Shimoda et al., 2018). In terms of function, the educational software can be categorized into three types: (1) attention-monitoring software, integrated with microcontrollers (Lestari et al., 2020) and online learning platforms (Chen et al., 2017; Liao et al., 2019) with the attentional state of learners simultaneously displayed on screens during learning; (2) attention-promoting software, with feedback-like questions (Kuo et al., 2017), visual reminders (Chen and Huang, 2014; Chen and Wang, 2018; Esquicha-Tejada et al., 2020), and audio alarms (Lin et al., 2014; Sun and Yeh, 2017) delivered when low attention level was detected during learning; (3) adaptive learning software, with learning material dynamically adjusted according to the attentional state of learners

(Shimoda et al., 2018).

3.1.3. Signal quality validation of portable EEG devices

Five studies verified the signal quality of EEG derived from portable EEG in attentional tasks (Fig. 2a). Xu et al. (2022) reported that alpha activity recorded by portable EEG was comparable to that recorded by a lab-based EEG system. Similarly, Khng and Mane (2020) demonstrated that portable EEG can detect similar effects in the Flanker task as a laboratory-based EEG system. Three studies verified the signal quality of the commonly-used eSense algorithm by comparing its output with typical EEG power spectrum analysis (Bitner et al., 2020; Bitner and Le, 2022; Sadudeemeechaithaweechoke et al., 2017).

3.2. Question 2: what data collection methodologies are used in portable EEG studies of attention within educational settings?

The methodology of portable EEG data collection was summarized on the following five dimensions: participant sampling (i.e., sample group and size), testing sites, EEG recording duration, material and tasks, and portable EEG device. Fig. 3 summarizes the information. Testing sites and tasks were further summarized as research paradigms. Previous studies were conducted on students at various educational stages ranging from preschool to higher education, but many of them were college students (n = 23). Most studies sampled fewer than 40 participants and lasted no longer than 40 min.

We followed the suggestion by Janssen et al. (2021) to summarize the research paradigms: lab paradigms in mobile labs (n = 1), lab paradigms in naturalistic settings (n = 1), online paradigms in educational technology (n = 14), naturalistic paradigms in mobile labs (n = 11), naturalistic paradigms in naturalistic settings (n = 11). In studies utilizing online or naturalistic paradigms, students were required to accomplish normal learning tasks (e.g., watching instructional videos, listening to lectures, or reading texts) rather than classic cognitive tasks (e.g., go/no go task, n-back task). Mobile labs refer to testing sites specially prepared for portable EEG studies but outside laboratories (e.g., a quiet classroom). Compared to naturalistic settings, there is more experimental control (e.g., few disturbances or interactions) in mobile labs and participants are unfamiliar with the testing environment.

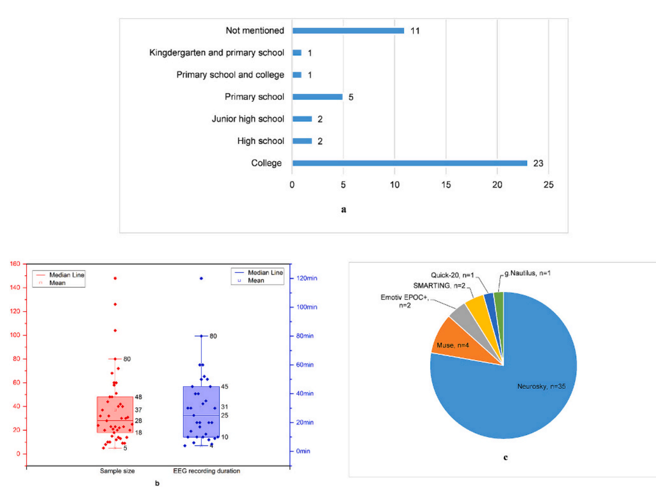

Fig. 3. EEG collection methodology Only data from portable EEG tests were extracted (e.g., when comparing the signal quality of portable EEG with traditional EEG, the information on traditional EEG collection was eliminated). **a**, the number of studies categorized by sample group. Information on the sample group was not available in eleven studies that were labeled as "not mentioned". The college group includes undergraduates and postgraduates. **b**, boxplots of sample size and EEG recording duration. Data on recording durations were not available in 12 studies. **c**, the proportion of portable EEG devices used. The "Neurosky" subgroup included studies utilizing the Mindwave Mobile and the Mindset.

The devices developed by Neurosky were the most frequently used (n = 35). The frequencies of the use of different portable EEG devices are shown in Fig. 3c. It is important to note that the specifications of these portable EEG devices have been systematically examined in other reviews (Lau-Zhu et al., 2019; Biondi et al., 2022; Niso et al., 2023; Xu and Zhong, 2018). These reviews provide comprehensive insights into key system specification factors as outlined by Bateson et al. (2017) to categorize portable EEG devices, including sampling rate, bit resolution, battery life, and electrode type.

3.3. Question 3: what EEG measures were used for measuring attention?

EEG measures were either selected using a theory-driven approach such as looking at EEG measures previously associated with attention (* labeled in Table 1, n = 8), or a data-driven approach such as by using machine learning or similar to identify EEG measures correlated with attention in their datasets (n = 37). Within the data-driven approach, 25 studies employed eSense, a commercial algorithm developed by Neurosky, which was categorized as a data-driven because "some parts of the eSense algorithm are dynamically learning" and "employ some 'slow-adaptive' algorithm" (eSense[tm] Meters, 2014). Other data-driven approaches used machine learning algorithms to find EEG measures shown in attentional states. Regardless of the approaches, most studies quantified task-related attention with the spectrum power in multiple EEG bands (e.g., normalized alpha power, low alpha power, the ratio of the alpha and beta power band, or relative theta and beta power).

Four studies measured attention with behavioral reports (e.g., attention self-rating questionnaires). The studies further examined the relationship between attention measured by portable EEG and behavioral reports. Inconsistent findings were reported. While several studies reported that attention indexed by EEG was positively correlated with behavioral measures (Grammer et al., 2021; Sun and Yeh, 2017) others reported a negative or no correlation (Chen et al., 2017; Dikker et al., 2020; Grammer et al., 2021).

4. Discussion

This scoping review synthesizes studies using portable EEG for measuring attention in educational settings with a focus on research aims, EEG collection methodology, and EEG measures. Below we summarize the main findings as well as discuss the challenges and opportunities in each area.

4.1. Research aims

Three research aims were identified. They were: evaluating the effects of learning-related factors on attention, developing algorithms and software to monitor and improve attention, and validating the data quality of portable EEG devices.

Most studies examined the influence of bottom-up factors (e.g., the salience of learning materials) on attention in educational settings but ignored the influence of top-down factors (e.g., the current goal of learners). Attention is typically governed by two types of control - top-down and bottom-up - where top-down control is guided by the current selection goals, and bottom-up control is driven by physical salience (Awh et al., 2012; Buschman and Miller, 2007; Corbetta and Shulman, 2002; Petersen and Posner, 2012). According to this dichotomy, the majority of reviewed studies focused on the bottom-up process, i.e., the learning context, such as the different presentation forms, the availability of learning aids, the physical environment, school activities, and different interactive activities. It should be noted that these bottom-up factors may be particularly salient in structured learning environments and may not generalize to other contexts. Future research should carefully consider the generalizability of findings from these controlled educational settings. Moreover, as top-down factors may interact with the bottom-up factors to affect attention (Awh et al., 2012), future studies could benefit from integrating top-down factors to understand if and how these internal factors influence the salience-driven effects of learning materials on attention. For example, the effect of the salience of learning material/context may be moderated by learning interest (Yang et al., 2015).

The effectiveness of attention-monitoring/promoting software needs further examination. Capitalizing on the advantage that portable EEG can measure live attention, several studies developed attention-monitoring software and provided an index of instantaneous attentional state to learners to promote learning (Chen et al., 2017; Chen and Huang, 2014; Chen and Wang, 2018; Kuo et al., 2017). However, the effectiveness of these techniques appears to depend on individual learner traits. For example, Kuo et al. (2017) found that learners with a preference for structured, sequential processing benefitted more from the feedback, while those with a more holistic approach saw less impact. Chen and Wang (2018) observed that gender differences influenced the effectiveness of attention-monitoring tools, with female students responding more positively to the attention-promoting feedback. Additionally, Sun and Yeh (2017) found that real-time attention feedback could interact with individual traits like sensitivity to feedback and anxiety. These studies highlight the importance of tailoring attention-monitoring feedback, suggesting that future research should focus on adapting these tools for varied educational profiles.

The signal quality of portable EEG has been verified in short recording durations, but there is little evidence regarding long-term signal quality. While portable EEG devices have been validated in different tasks (Chabin et al., 2020; Kam et al., 2019; Khng and Mane, 2020), sites (Edwards and Trujillo, 2021; Ladouce et al., 2019), and populations (McWilliams et al., 2021; Xu et al., 2022) with short recording duration (e.g. in 10 min), few studies investigated the long-term stability of portable EEG devices. The main challenge of long-term portable EEG recording is keeping the impedance stable. For devices with dry electrodes (e.g., the Mindwave Mobile), sweat and movements may be the primary factors affecting stability. While for semi-dry electrodes (e.g., the Emotiv EPOC system), the electrode-skin impedance may fluctuate due to unstable electrolyte release. Since researchers are interested in monitoring attention in long-recording durations (e.g., during a whole class), verifying the long-term validity of portable EEG is crucial.

4.2. EEG collection methodology

We decoded previous studies regarding participant sampling, testing sites, material and tasks, recording duration, and portable EEG devices. Our results are in line with an earlier review (Xu and Zhong, 2018) in that (1) undergraduates and postgraduates were the most frequent participants, (2) the portable EEG devices developed by NeuroSky were most used, and (3) the majority of the EEG recordings lasted less than 40 min.

Most studies were semi-naturalistic, involving representative participants and stimuli that were carefully sampled to mimic the real learning settings. While researchers often assume that attentional processes are mainly involved in these contexts, it is likely that they also involve a range of other cognitive processes that frequently co-occur with attention and share overlapping neural mechanisms—for example, working memory (Gazzaley and Nobre, 2012). This overlap complicates the interpretation of EEG data, as it may capture a blend of attentional and non-attentional activity. Future studies would benefit from refining research designs to better target specific types of attention (e.g., sustained or selective attention) by incorporating tasks or stimuli that isolate these processes more effectively and use EEG indices more specific to attention.

Meanwhile, semi-naturalistic settings may be insufficient to capture the inherent elements of real-world learning. Semi-naturalistic research may miss essential elements of real-world learning, such as the multisensory and unstructured inputs, the dynamic interactions between familiar peers and teachers, the active engagement of learners, and the naturally occurring distractions in a classroom (Janssen et al., 2021). Therefore, there is a growing need to adapt semi-naturalistic research to fully-naturalistic settings (i.e., in the regular real-world learning environment). Real-world research can generate valuable insights. For instance, in teacher-led classroom lectures, students who reported higher closeness with the teacher exhibited higher student-teacher EEG synchrony and achieved better learning performance (Bevilacqua et al., 2019).

The three-stage cyclical model proposed by Janssen et al. (2021) suggests a workflow that contributes to adapting portable EEG studies in fully-naturalistic settings and drawing causal inferences in educational studies. Hypotheses derived from correlational studies could be first examined in labs or semi-naturalistic settings. The results of this process can be used to guide the selection of variables in fully-naturalistic research settings by identifying candidate variables that have an impact on learning. By generating and cyclically testing hypotheses, researchers can gradually refine their understanding of the relationship between instructional factors and learning.

Admittedly, applying portable EEG in fully-naturalistic educational settings is challenging. The first challenge is ensuring the quality of EEG data. While it has been validated using well-established laboratory paradigms, more evidence on validations in the naturalistic learning context is needed, as the EEG recordings can involve a substantial number of artifacts caused by natural interactions in real-world learning, such as eye movements, blinks, nodding, gestures, facial expressions, and discussions. Notably, Xu et al. (2022) compared the EEG data quality recorded by traditional (wired) EEG in a traditional EEG laboratory and by portable (wireless) EEG in classrooms with normal instructional activities. To compensate for the artifacts, longer recording time, more trials, and sufficient scalp coverage are recommended (Janssen et al., 2021; Xu et al., 2022). Beyond managing artifacts, verifying the signal quality of EEG is challenging, especially in naturalistic educational settings where real-world conditions add layers of complexity beyond traditional lab environments. Open science practices (e.g., data and code sharing), provide a pathway to addressing these challenges. By facilitating collaborative validation, enhancing transparency, and refining analytical methods, open science strengthens the rigor and reproducibility of EEG research (Pernet et al., 2020), building the foundation needed for reliable applications in educational contexts.

The second challenge is causality inference. As mentioned before, multiple undefined factors impact learning in fully naturalistic educational settings and as a result, it is challenging to determine which factors cause outcomes. Effective collaboration with educators (e.g., teachers, school administrators, and education policymakers) is necessary to understand the constituents of real-world learning processes and to evaluate them. For example, the effectiveness of different classroom activities can be assessed in structured classes that follow course schedules with the help of teachers (Dikker et al., 2017, 2020).

4.3. EEG measures

The most prevailing approach to capturing attention is based on the eSense algorithm, which needs further attention. The eSense algorithm is specially developed to analyze the EEG data recorded by the portable EEG devices from NeuroSky Inc. It outputs attention value on a scale of 0 to 100, where a higher score means a more elevated attentional state. This straightforward interpretation of attention and their low costs make the portable EEG devices developed by NeuroSky Inc. the most popular in assessing attention in education. However, the eSense algorithm is proprietary and functions as a 'black-box,' lacking transparency in how it processes EEG signals in detail. This poses challenges for researchers, as it prevents full access to the underlying processing methods, limiting the ability to validate the algorithm or understand the precise neural mechanisms it reflects. This opacity also restricts researchers from adapting or refining the algorithm to incorporate recent advances in EEG analysis, such as phase-based or connectivity-based measures of attention. These limitations highlight the need for open-access alternatives that provide researchers with full control over data processing and algorithmic transparency, enabling reproducibility and scientific accountability (Ananny and Crawford, 2018). Customized algorithms using machine learning are emerging as promising alternatives. However, empirical evidence is still needed to examine the efficacy and effectiveness of these custom-developed and transparent methods for capturing attention.

Another problem arises with the prevalence of NeuroSky's portable EEG devices. Previous studies mainly used frontal EEG recording and thus may only be measuring a subcomponent of attention. Attention is a complex construct that encompasses three networks, namely alerting, orienting, and executive attention (Petersen and Posner, 2012). The majority of studies utilizing single-channel frontal EEG recordings primarily reflect executive attention. Despite some studies employing multi-channel EEG devices, the attentional network under examination was limited to a single domain, such as the orienting network (Grammer et al., 2021; Xu et al., 2022), or the alerting network (Dikker et al., 2020).

Since successful learning depends on the cooperation between the three types of attention (Dehaene, 2020), focusing on only one type of attention is problematic. During learning, learners must engage by arousing the brain's alerting network, direct and amplify their attentional focus like “spotlights” using the orienting network, and selectively activate effective cognitive processes with the executive attention network (Dehaene, 2020). In this sense, multi-channel portable EEG devices are more appropriate for simultaneously measuring the extensive attention networks including the right hemisphere systems related to alerting, the frontal and posterior areas related to orienting, and the connections from the midline cortex and the anterior cingulate cortex related to the executive attention(Petersen and Posner, 2012). Successful learning requires the coordination of the three attention networks, future studies need to clarify whether the multi-channel recording is advantageous in measuring different types of attention.

Note that while preliminary evidence exists supporting a correlation between EEG and subjectively reported attention levels (McCabe et al., 2020), the low/no correlation between attention measured by portable EEG and attention measured by behavioral approaches merits further investigation. One explanation is that they capture attention in different ways. For instance, the alpha power may capture attentional processes related to both local (i.e., the orienting attention) and global neural activity (i.e., the alerting state) whereas behavioral measures (i.e., self-reported focus) may reflect more complex cognitive processes, including those related to environmental and contextual factors (e.g., sleepiness, distractions) (Dikker et al., 2020). Another explanation could be measurement errors. The variability and reliability of EEG-based attention can be affected by technical factors such as electrode types and placement, and signal quality (as discussed in Sections 4.1 and 4.2). Similarly, the measurement of attention through observer ratings and self-reported questionnaires may be subject to inaccuracies due to individual biases and expectations. Therefore, it is important to consider the specific attention components assessed and the possible measurement errors when interpreting and comparing EEG and behavioral measures of attention.

Another challenge for employing EEG indicators of attention is how to effectively assess the dynamic interactions during teaching and learning. We note a new EEG measure called brain-to-brain synchrony or interpersonal neural synchronization. Recently, there have been several studies employed this measure to investigate the effects of teacher-student interaction (Dikker et al., 2017) and student-student interaction (Bevilacqua et al., 2019). A meta-analysis verified the effectiveness of interpersonal neural synchronization (INC) in predicting learning outcomes (Zhang et al., 2022). However, the brain mechanism of INC is not clear, thus relevant studies were excluded from this review. Some researchers speculated shared attention as a possible underlying mechanism (Dikker et al., 2017). Future studies are needed to investigate how attention fluctuates in the natural interactions between learners, instructors, and the environment, and further, reveal the brain mechanisms underlying these interactions.

5. Conclusion

The varied research aims and methodologies appear to pose a challenge to educational neuroscience, a field in its infancy. This scoping review aimed to bridge the methodological knowledge gap by clarifying the research aims, EEG collection methodologies, and EEG measures of studies on applying portable EEG devices to assess attention while learning. Portable EEG makes it possible to monitor and promote attention during naturalistic educational settings. However, it remains challenging to obtain high-quality EEG recordings, infer causality, and measure the dynamic interactions in naturalistic learning contexts. Future studies are needed to verify the long-term stability of portable EEG devices and reveal the brain mechanisms of natural learning interactions.

CRediT authorship contribution statement

Jian-Wei Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Da-Wei Zhang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Stuart J. Johnstone:** Writing – review & editing, Writing – original draft, Validation, Methodology, Conceptualization.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

The data involved in the flowchart for retrieval and screening process and Appendix Table 1 is available from the corresponding author upon reasonable request.

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