

RESEARCH ARTICLE

Dry EEG in Educational Neuroscience: Measurement Quality, Methodological Rigor, and Educational Applications

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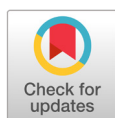
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ABSTRACT

Dry electroencephalography (EEG) offers a practical means of measuring rapid neural dynamics in educational research without conductive gels or pastes, but procedural convenience should not be equated with superior signal quality or direct access to cognitive states. This integrative narrative review examines measurement characteristics, methodological rigor, and educational applications of dry EEG and includes an empirical pilot study with 10 adults. Comparative evidence indicates that dry EEG can reduce preparation and cleanup demands, whereas signal quality varies with electrode-skin contact, movement, participant characteristics, device architecture, and recording context. Methodological rigor depends on matching the research question and target EEG feature with the task, participants, recording system, quality-control procedures, preprocessing, and level of inference. Educational applications include attention, engagement, cognitive load, neurofeedback, and social interaction, with dry EEG used to track time-varying EEG features, compare learning conditions, and support repeated or multi-person recording. In the pilot, exploratory paired comparisons showed higher relative gamma-band power for infographic-based than text-based materials at Fp1, Fp2, Pz, and O1; these differences were interpreted as scalp-level condition effects. Dry EEG is most informative when selected for a clear measurement purpose, device-specific limitations are reported transparently, and neural findings are interpreted alongside behavioral, performance, and self-report evidence.

Keywords: Educational neuroscience, dry EEG, practical application of dry EEG, neurofeedback, brain-based education



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Introduction

Need of Study

Educational neuroscience integrates behavioral and neural evidence to understand learning and educational processes (Orovas et al., 2025). Performance and self-report measures provide important information about learning outcomes and subjective experience, but learning-related processes can change rapidly during task performance and may not be observable from these

measures alone. EEG therefore provides complementary information about the temporal dynamics of neural activity during learning, attention, or task performance. Among available methods, EEG is particularly well suited to questions requiring millisecond-scale temporal resolution and can be deployed in settings ranging from controlled laboratories to increasingly naturalistic learning environments (García-Monge et al., 2024; Yang et al., 2025).

Dry EEG is defined by the absence of a separately applied conductive medium such as gel or paste. Compared with conventional wet EEG, this feature can reduce preparation and cleanup demands and may facilitate repeated measurements in educational research. These practical advantages, however, do not guarantee stable recording quality, because dry EEG remains sensitive to electrode–skin contact, impedance, movement, participant characteristics, and device architecture. Dry, mobile, portable, and wireless are not interchangeable descriptors: dry versus wet refers primarily to the electrode–skin interface and conductive medium, whereas mobility and wireless transmission describe the broader recording system (Xiong et al., 2025; Yang et al., 2025). A portable headset may use wet electrodes, and a dry system may still be used in a stationary laboratory protocol. When dry electrodes are used within a mobile or wireless system, movement-related changes in electrode contact and transmission stability may affect the same recording, and these sources of measurement error should be distinguished. Accordingly, the feasibility of EEG recording in naturalistic educational settings should be understood as a function of the electrode characteristics, the broader recording system, and the study design rather than as an inherent property of dry electrodes alone.

Educational reviews have primarily addressed EEG hardware, methods, and applications in naturalistic educational contexts (García-Monge et al., 2024; Orovas et al., 2025; Yang et al., 2025), whereas technical reviews have emphasized dry-electrode materials, impedance, contact mechanics, noise, and device architecture (Bayat et al., 2026; Xiong et al., 2025). However, these areas have remained insufficiently connected, limiting integrated guidance on how dry EEG measurement characteristics should inform task design, quality control, preprocessing, analysis, and educational interpretation. This review addresses this gap by integrating measurement characteristics, methodological rigor, and educational applications. Accordingly, this review examines (a) measurement characteristics of dry EEG relative to wet EEG, (b) methodological considerations for the rigorous use of dry EEG in educational neuroscience, and (c) educational applications of dry EEG, and includes an empirical pilot study applying dry EEG to an educational task.

Review Approach

Literature published since 2000 was identified through Google Scholar between August 5 and 22, 2026, using English terms related to EEG type and electrode format, including EEG, electroencephalography, dry EEG, wet EEG, semi-dry EEG, and dry electrode, together with educational application terms such as student, attention, engagement, cognitive load, hyperscanning, and neurofeedback. Retrieved sources were screened by title and abstract, followed by full-text examination of potentially relevant sources. Sources were included when they directly addressed at least one of three areas: measurement characteristics of dry and wet EEG; methodological considerations concerning dry EEG acquisition, preprocessing, analysis, or interpretation; or educational applications of dry EEG. Sources were excluded if their purpose or methods could not be determined from the full text, insufficient information was available for evaluation, or they fell outside the review scope. The selected literature was synthesized across these areas.

Characteristics of Dry EEG

Electrode–Skin Interface and System Design

The measurement characteristics of dry EEG depend on both the electrode–scalp interface and the design of the recording system. EEG records voltage differences at the scalp that arise from synchronized neural electrical activity transmitted through biological tissue. For both dry and wet systems, signal acquisition depends on electrode placement, reference configuration, amplification, and the electrical properties of the electrode–skin interface. Dry electrodes acquire signals without separately applied conductive gel or paste and may use direct-contact or capacitive approaches. Systems may also use passive electrodes or active circuitry near the electrode to buffer high-impedance signals (Bayat et al., 2026; Xiong et al., 2025). Thus, the label dry EEG encompasses heterogeneous devices rather than a single standardized measurement technology, and their measurement characteristics should be considered in relation to contact method, amplification, and system design.

Electrode–skin impedance reflects opposition to signal flow at the interface and varies with contact quality and signal frequency. Dry systems often operate at higher impedance than conventional wet systems, making amplifier input impedance, contact stability, and shielding important design considerations. Hair, scalp properties, head shape, pressure at the electrode, and movement can all alter contact over time (Bayat et al., 2026; Xiong et al., 2025). Consequently, an acceptable initial impedance value is not sufficient evidence that signal quality will remain stable across a learning session, particularly in educational tasks where participant movement may alter electrode contact.

Practical Advantages and Signal-Quality Trade-Offs

The clearest practical advantage of dry EEG is avoiding gel application and post-recording cleanup. Comparative studies report shorter setup for some dry systems, although benefits depend on channel number, cap design, participant fit, and comparison procedures (Fiedler et al., 2023; Hinrichs et al., 2020; Kam et al., 2019). Thus, compared with wet EEG, the most consistent advantage of dry EEG is procedural rather than electrophysiological, and this reduction in procedural burden can be relevant in educational studies that involve repeated sessions, multiple participants, or settings in which extensive preparation is disruptive.

Ease of use, however, does not imply superior electrophysiological performance. Dry recordings can show higher impedance, greater noise, lower signal-to-noise ratio, or greater sensitivity to contact changes than wet recordings, and performance differs across systems and frequency ranges (Ehrhardt et al., 2024; Fiedler et al., 2023; Hinrichs et al., 2020; Mathewson et al., 2017). High input-impedance amplifiers and active electronics can mitigate some consequences of high electrode impedance, which is why impedance thresholds should be interpreted in relation to device architecture rather than as universal quality cutoffs. Comfort is similarly device dependent: some dry-electrode designs may cause pressure- or pin-related discomfort during prolonged recording, whereas other users may prefer dry systems because they avoid gel (Hinrichs et al., 2020; Xiong et al., 2025).

These trade-offs are particularly consequential for educational populations. Much of the dry-versus-wet validation literature has relied on healthy adults, relatively small samples, and short recordings. Generalization to children,

adolescents, dense hair types, extended lessons, repeated testing, and highly mobile activities is therefore limited (Bayat et al., 2026). Device selection should therefore be based on the fit among the research question, participant population, recording duration, movement demands, and required signal features, rather than the ease with which a system can be applied.

EEG Features Available With Dry Systems

Dry EEG can support the major classes of EEG analysis used in educational neuroscience, including spectral power and event-related potentials (ERPs), provided that the selected system delivers adequate signal quality for the target feature. Spectral analysis summarizes power across frequency ranges, commonly theta, alpha, beta, and gamma bands. However, band boundaries vary across studies, and no frequency band should be treated as a one-to-one marker of a single cognitive or emotional state (Keil et al., 2022; Orovas et al., 2025). Comparative studies have reported relatively similar alpha- and beta-band power between dry and wet EEG, with higher low-frequency (delta and theta) power in dry recordings (Fiedler et al., 2023; Hinrichs et al., 2020; Kam et al., 2019). Correspondence in the gamma band has been evaluated far less systematically: Some dry–wet comparisons restricted their main analyses to 30 Hz or below (Ehrhardt et al., 2024; Hinrichs et al., 2020), so agreement above that range remains largely uncharacterized. Correspondence observed in one frequency band should therefore not be assumed to generalize across the spectrum.

ERPs quantify voltage changes time-locked to events and can be characterized by component amplitude, latency, and scalp distribution. Dry systems have reproduced several ERP components, including P3/P300 and sensory evoked responses, but equivalence with wet EEG is not guaranteed. Comparative studies have reported both broadly similar components and differences in noise, amplitude, latency, or statistical sensitivity under specific recording conditions (Ehrhardt et al., 2024; Fiedler et al., 2023; Hinrichs et al., 2020; Mathewson et al., 2017). The relevant question is therefore not whether dry EEG can record EEG in general, but whether a particular device can measure the feature of interest with sufficient quality and reliability under the intended educational conditions. Representative frequency ranges and interpretive considerations are summarized in Table 1.

Table 1. Representative EEG Frequency Bands and Interpretive Considerations

Band	Approximate range	Interpretive consideration in educational research
Delta (δ)	0.5–4 Hz	Slow activity; especially sensitive to drift and movement-related contamination in field recordings.
Theta (θ)	4–8 Hz	Frequently examined in working-memory and cognitive-load paradigms; meaning depends on task, location, and analysis.
Alpha (α)	8–12 Hz	Often examined in relation to visual attention and task engagement; changes are not specific to a single construct.
Beta (β)	12–30 Hz	Used in studies of attention and task performance; interpretation should consider muscle and movement artifacts.
Gamma (γ)	30–45 Hz or higher	High-frequency activity can be cognitively informative but should be interpreted conservatively because artifact sensitivity is substantial.

Note. Frequency boundaries vary across studies and systems. The ranges shown are representative; the frequency bands used in the pilot analysis differ slightly (e.g., delta 1–4 Hz after 1–45 Hz band-pass filtering). Frequency bands are context-dependent analytic ranges, not direct labels for cognitive states (Keil et al., 2022; Orovas et al., 2025).

Methodological Considerations of Dry EEG

Data Acquisition and Ongoing Quality Control

Because these features and their interpretive limits depend on how the data were obtained, the decisions surrounding acquisition and analysis matter as much as the choice of device. Dry EEG does not require a particular experimental paradigm. Block, event-related, resting-state, and naturalistic designs should be selected according to the research question, required temporal precision, and learning activity. Naturalistic tasks may improve contextual relevance but also increase eye movements, facial and neck muscle activity, body movement, and changes in electrode contact and impedance. Controlled and naturalistic designs therefore offer different inferential strengths rather than a simple hierarchy of realism (García-Monge et al., 2024; Yang et al., 2025).

Before recording, researchers should document the electrode montage, reference, sampling rate, amplifier characteristics, signal-quality criteria, and procedures used to improve contact. During recording, signal quality should be monitored continuously. Movement, electrode adjustments, environmental disturbances, and task changes should be logged to contextualize later artifact decisions. Wireless transmission also requires verification of connection stability and data integrity.

Educational studies also benefit from synchronized non-EEG measures. Behavioral, task-event, self-report, or observational measures can clarify whether an EEG-derived effect corresponds to the intended construct. Because attention, engagement, and cognitive load are multidimensional, such measures help prevent a physiological feature from being treated as the construct itself (Orovas et al., 2025; Yang et al., 2025).

Preprocessing, Data Quality, and Reliability

The analytical principles for dry and wet EEG are similar, but dry recordings may place greater demands on quality control when contact varies or movement is present. Preprocessing commonly includes filtering, artifact identification or correction, removal or interpolation of problematic channels, epoching, and re-referencing (Chaddad et al., 2023). Filter parameters should be selected for the target signal and reported because inappropriate filtering can distort temporal and spectral features (Keil et al., 2022). Independent component analysis can isolate ocular and other stereotyped artifacts in multichannel data, but its performance depends on the amount and dimensionality of available data and should not be applied mechanically (Chaumon et al., 2015).

Signal quality and reliability should be evaluated as related but distinct properties. Artifact burden, rejected channels or epochs, and signal-to-noise characteristics indicate data usability, whereas split-half or test-retest analyses address consistency within or across sessions (Lopez et al., 2023). This distinction is particularly important when repeated measurements compare conditions or track change over time. A visually clean recording does not establish that an EEG metric is sufficiently stable for individual-level inference.

Analysis and Interpretation

Spectral analyses should specify the frequency ranges, transformation procedures, absolute or relative power definitions, and statistical comparisons used. Relative power can reduce between-person differences in overall amplitude

but introduces dependence on the denominator frequency range, whereas absolute power retains amplitude information but can be more affected by individual and recording differences. Time-frequency analyses may be useful when learning-related changes unfold rapidly within trials (Keil et al., 2022). Frequency-band labels should not be treated as direct indicators of an educational construct; their interpretation should be grounded in the construct's operational definition, as well as the task and analytic context (Keil et al., 2022).

ERP studies require accurate event timing, sufficient artifact-free trials, and a predefined component definition. Component amplitude and latency should be linked to task literature rather than assigned generic meaning. Likewise, scalp topographies do not identify the cortical region beneath an electrode; source localization requires forward and inverse models and remains an estimate, not a direct measure of regional activation. Connectivity measures should be interpreted conservatively because sensor-level dependence can reflect common sources or functional interaction.

EEG features should therefore be kept conceptually distinct from the educational constructs they are used to examine. An EEG feature is a physiological measurement derived under a particular task and analytic pipeline; attention, engagement, cognitive load, and learning are theoretical constructs inferred from multiple forms of evidence. This distinction should be made explicit by defining the construct, justifying the selected EEG feature, reporting data-quality and preprocessing decisions, stating the statistical model, and interpreting neural results together with behavioral or self-report measures.

Educational Applications of Dry EEG

Dry EEG has been applied to several constructs central to educational neuroscience, but the evidence remains heterogeneous in devices, tasks, signal features, and operational definitions. EEG-derived cognitive-load estimates have been related to task and scaffolding difficulty during science learning, with higher load associated with poorer performance in some models (Mills et al., 2017). In a classroom-oriented dry-electrode study, theta-related activity varied with working-memory demands, illustrating the feasibility of tracking load-related changes under educationally relevant conditions (Lee et al., 2021). These findings suggest sensitivity to task demands but do not establish a universally applicable neural measure of cognitive load.

Attention and engagement are promising but conceptually demanding applications. During curricular video-based learning, beta-band power was significantly associated with academic performance in secondary-school students using a single-channel (Fp1) consumer-grade dry-electrode headset (Fuentes-Martinez et al., 2023). Personalized dry EEG neurofeedback during online teaching was followed by a short-term increase in attention-related outcomes (Senova et al., 2026). EEG-derived engagement has also been used to compare learning conditions; in medical education, mixed-reality learning was associated with differences in engagement and cognitive-load measures relative to tablet-based learning (Noel et al., 2025). Across these studies, the construct definition and algorithm used to derive the EEG index are as important as the headset itself.

Beyond single-learner applications, mobile educational EEG reviews have highlighted multi-person recording, classroom interaction, and hyperscanning as emerging directions (Yang et al., 2025). Dry EEG hyperscanning has been used during parent-child cooperation and competition (Marzoratti et al., 2023) and during triadic cooperative and

noncooperative decision-making, in which changes in social beliefs were accompanied by changes in intra- and inter-brain neural dynamics (Kim et al., 2026). These studies indicate that dry EEG can examine dyadic and group-level neural dynamics. However, apparent inter-brain coupling can also reflect shared sensory input, common task structure, or coordinated behavior rather than interpersonal processes alone. Inter-brain measures should therefore be interpreted with behavioral and interaction data rather than treated as direct indicators of sociality or shared understanding.

Across these applications, a consistent pattern emerges: dry EEG is informative about how EEG features vary across learning conditions, but it is not a stand-alone diagnostic technology. The scientific value of these data still depends on construct validity, signal quality, analytic transparency, and convergence with non-EEG evidence.

A Practical Application of Dry EEG

Measurement Procedures

To provide preliminary empirical evidence on the application of dry EEG to an educational task, a pilot study was conducted with 10 adults experienced in educational settings and neuroscience research ($M = 35.9$ years, $SD = 8.83$, range 29–60; five men and five women, all right-handed). Before the task, all participants provided written informed consent after receiving a detailed explanation of the study procedures. The forehead and earlobes were cleaned, accessories were removed, and participants were seated in a noise-controlled room facing the stimulus monitor. EEG signals were recorded using the iSyncWave dry EEG system (iMediSync Inc.; K220056), an FDA-cleared 19-channel system with Ag/AgCl-coated conductive polymer electrodes positioned according to the international 10–20 system (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2), a PPG sensor on the right earlobe, and a reference electrode on the left earlobe. Signals were acquired at 250 Hz over 0.5–50 Hz, and electrode impedance was checked and adjusted before recording. After the task, data storage was verified, and participants completed a post-measurement interview and questionnaire.

Task Design

The task used a block paradigm to examine EEG activity while participants read neuroscience materials in text-based or infographic formats. Twelve materials covering neuroscience topics, including mirror neurons, comprised six text-based (G1) and six infographic-based (G2) stimuli. All materials were presented in Korean, the participants' native language; both formats covered the same topics and key content, with comparable character count, font, and color schemes. Each stimulus was presented for 40 s and followed by a 10-s fixation period. Stimuli were presented as six G1–G2 pairs with within-pair order counterbalanced. Same-format stimuli therefore sometimes appeared consecutively across pair boundaries to reduce anticipation and strict alternation effects. The task paradigm is illustrated in Fig. 1.

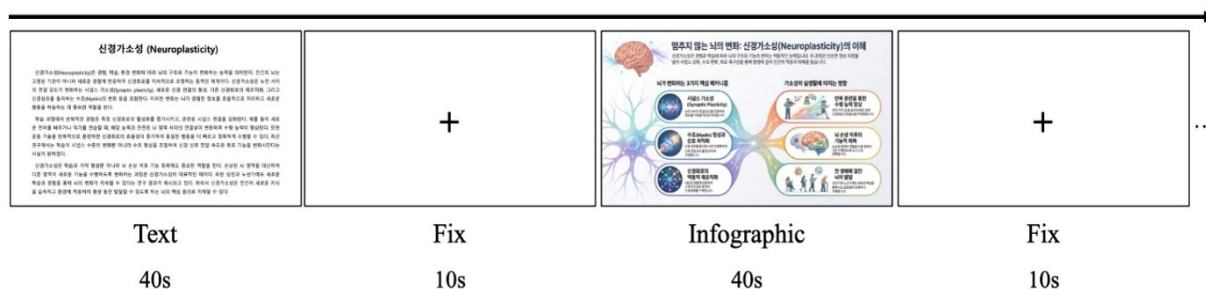


Fig. 1. Task paradigm used in the practical dry EEG application

Data Preprocessing and Analysis

EEG activity during the two learning-material conditions was analyzed using iSyncBrain® v3.0.1 (iMediSync Inc., Republic of Korea), a cloud-based automated analysis platform for iSyncWave. Before upload, event intervals and trial labels were adjusted using EDFbrowser v2.15. In iSyncBrain, EEG signals were preprocessed using a 60-Hz notch filter and a 1–45 Hz band-pass filter. The platform's AI-based analysis engine performed independent component analysis (ICA) and automatic denoising to identify and remove non-neural artifact components, including ocular artifacts such as eye blinks, without manual component selection by the researchers.

Following preprocessing, power spectral density was estimated using the Fast Fourier Transform (FFT) for the 19 electrodes. Spectral power was calculated for delta (1–4 Hz), theta (4–8 Hz), alpha1 (8–10 Hz), alpha2 (10–12 Hz), beta1 (12–15 Hz), beta2 (15–20 Hz), beta3 (20–30 Hz), and gamma (30–45 Hz). The alpha and beta subdivisions represent the frequency ranges adopted for this pilot analysis rather than universal EEG band boundaries. Relative power for each band and electrode was calculated by dividing the power within each frequency band by total spectral power from 1 to 45 Hz. The resulting condition-specific relative-power values were exported from iSyncBrain, and their spatial distributions were visualized using topographic maps.

As an exploratory analysis, relative gamma-band power was compared between the text-based (G1) and infographic-based (G2) conditions at each of the 19 EEG electrodes using two-tailed paired-samples *t*-tests. Relative gamma-band power was significantly higher in G2 than in G1 at Fp1 ($t(9) = 2.997, p = .015, d_z = 0.948$), Fp2 ($t(9) = 2.394, p = .040, d_z = 0.757$), Pz ($t(9) = 2.592, p = .029, d_z = 0.820$), and O1 ($t(9) = 2.374, p = .042, d_z = 0.751$). These findings indicate higher relative gamma-band power during the reading and comprehension of infographic-based materials at the bilateral prefrontal sites Fp1 and Fp2, the midline parietal site Pz, and the left occipital site O1 (Fig. 2).

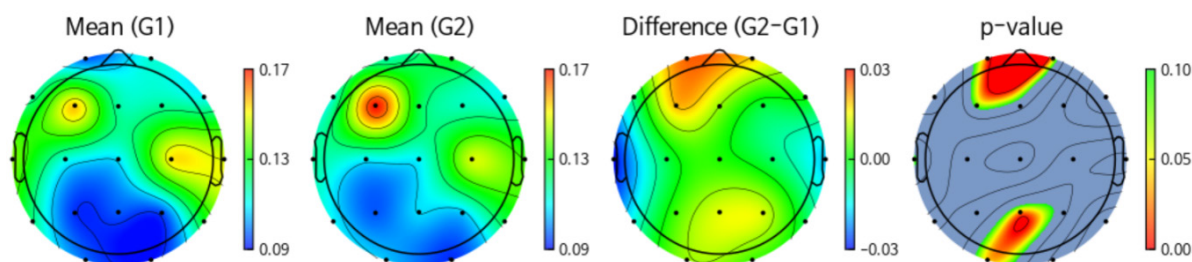


Fig. 2. Relative gamma-band power by learning-material condition (G1 = text-based materials; G2 = infographic-based materials).

Interpretation of Results

These condition-related differences in relative gamma-band power require cautious interpretation. Higher relative gamma-band power at Fp1, Fp2, and O1 may align with associations between gamma activity and higher-order cognition, attention, learning, and memory (Kaiser & Lutzenberger, 2005; Orovas et al., 2025). The Pz finding may also be considered in relation to previous evidence linking frontal–parietal EEG activity to visual feature integration (Phillips et al., 2012). However, these associations do not support a one-to-one inference from increased gamma-band power to greater attention, engagement, or learning, and scalp activity at a given electrode cannot be attributed directly to the cortical region beneath that electrode. These results are therefore best interpreted as a condition-related difference in scalp-level relative gamma-band activity rather than direct evidence of stronger activation in a specific cortical region or cognitive function.

Interpretation also requires the measurement constraints described earlier. Dry EEG is sensitive to electrode–scalp contact and movement, and frontal sites such as Fp1 and Fp2 are particularly vulnerable to ocular activity. Moreover, this pilot used a small adult sample and a within-participant comparison of two material formats. Accordingly, the present findings are best treated as preliminary and specific to this sample and these materials, and they do not establish that infographic formats inherently produce greater cognitive engagement than text-based formats.

Discussion

The evidence reviewed here indicates that the principal advantage of dry EEG lies in procedural practicality rather than inherently superior neurophysiological performance. Removing conductive media can simplify setup and cleanup, but signal fidelity, comfort, and stability remain device- and context-dependent. Agreement with wet EEG also varies across systems and signal features, so procedural convenience should not be equated with superior signal quality or suitability for naturalistic educational settings (Fiedler et al., 2023; Hinrichs et al., 2020; Kam et al., 2019).

These measurement characteristics directly affect research design, acquisition, analysis, and interpretation. Dry EEG does not require a unique analytical framework; established EEG methods remain applicable but demand careful attention to contact quality, movement, device architecture, and transparent preprocessing. Researchers should begin with the educational question and target EEG feature, select the device and task accordingly, monitor signal quality and relevant behavior during acquisition, report preprocessing and data loss, and keep conclusions at the level supported by the design. Naturalistic tasks may increase contextual relevance but also increase ocular and muscle activity, body movement, and changes in electrode contact. The pilot findings reinforce the need for conservative interpretation of scalp-level EEG differences rather than direct inference about cortical localization or educational constructs (Keil et al., 2022; Orovas et al., 2025).

Under these conditions, dry EEG can support studies that track time-varying EEG features during learning, compare learning conditions, and involve repeated measurement, real-time neurofeedback, or simultaneous recording from multiple participants. However, attention, engagement, cognitive load, and learning should not be inferred from a single EEG feature and are better interpreted alongside behavioral, performance, or self-report evidence. Further validation is needed in children and adolescents, across diverse hair and scalp characteristics, and during prolonged and repeated

measurements (Bayat et al., 2026; Lopez et al., 2023; Xiong et al., 2025). Social-interaction research should also be extended to educational dyads and groups, with inter-brain measures interpreted together with synchronized behavioral and interaction data (Kim et al., 2026; Marzoratti et al., 2023; Yang et al., 2025). Because this review used a narrative Google Scholar search and synthesized heterogeneous studies, the literature should not be interpreted as exhaustive or quantitatively comparable. Overall, the value of dry EEG depends on matching the research question, participants, task, device, environment, target EEG feature, and level of inference.

Conclusions

Dry EEG can broaden educational neuroscience methods by reducing gel-related preparation and enabling repeated or context-sensitive acquisition. These advantages do not ensure signal quality or valid educational interpretation. Signal quality and comfort vary across devices and participants, movement and contact changes remain consequential, and EEG-derived features do not map uniquely onto educational constructs. The pilot provides preliminary evidence of condition-related differences in scalp-level spectral activity between learning-material formats, reinforcing conservative interpretation. Dry EEG is therefore best suited to tracking EEG changes during learning, comparing learning conditions, or supporting repeated sessions, real-time neurofeedback, or simultaneous multi-learner recording. Such use requires transparent quality control and preprocessing, with interpretation alongside behavioral, performance, and self-report evidence. Ultimately, the educational value of dry EEG depends less on convenience than on appropriate measurement design and evidence-supported interpretation.

Conflicts of Interest

The authors declared no conflicts of interest.

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