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Wearable EEG Devices For Cognitive Monitoring And Diagnosis: A Systematic Review Of Advances, Applications, And Challenges

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Abstract

Wearable electroencephalography (EEG) devices have emerged as transformative tools in the fields of cognitive monitoring and neurological diagnosis, offering non-invasive, real-time assessment of brain activity in both clinical and non-clinical environments. Unlike conventional EEG systems that require bulky setups and specialized environments, wearable EEG technologies—ranging from headbands and ear-centered grids to textile-integrated electrodes—enable continuous and unobtrusive brain monitoring, thereby expanding opportunities for early detection, long-term assessment, and personalized interventions in conditions such as Alzheimer's disease, mild cognitive impairment, epilepsy, and cognitive workload-related disorders. This systematic review, conducted in accordance with PRISMA 2020 guidelines, synthesizes findings from peer-reviewed studies published between 2010 and 2025, retrieved from PubMed, Scopus, IEEE Xplore, and Web of Science, to critically evaluate the diagnostic accuracy, signal quality, usability, and clinical applicability of wearable EEG devices for cognitive assessment. A total of 78 studies met the inclusion criteria, encompassing both diagnostic and monitoring applications, with varied methodological approaches ranging from signal processing algorithms and machine learning classifiers to multimodal sensor integration. Findings indicate that wearable EEG systems demonstrate high potential for early-stage cognitive decline detection, real-time workload monitoring, and neurorehabilitation, although challenges remain in artifact reduction, electrode-skin interface stability, and standardization of data interpretation. Moreover, integration with mobile health platforms and cloud-based analytics is accelerating the shift toward patient-centric, home-based neurological care. However, heterogeneity in device specifications, study designs, and cognitive assessment protocols limits cross-study comparability, underscoring the need for standardized validation frameworks and multi-centric trials. The review concludes that while wearable EEG technology is poised to revolutionize cognitive diagnostics and monitoring, future advancements must focus on improving long-term wearability, enhancing signal robustness in real-world environments, and establishing regulatory and ethical guidelines to ensure safe and equitable adoption in both healthcare and everyday life applications.

Keywords: *Wearable EEG, Cognitive monitoring, Neurological diagnosis, Alzheimer's disease, Epilepsy, Mild cognitive impairment, Neurorehabilitation, Mobile health*

INTRODUCTION

Background

Electroencephalography (EEG) has long been regarded as one of the most accessible, non-invasive, and temporally precise techniques for recording brain activity [1]. By capturing voltage fluctuations from the scalp that reflect underlying cortical neuronal oscillations, EEG enables researchers and clinicians to study brain function in real time with millisecond resolution [2]. Historically, EEG systems have been bulky, tethered to clinical laboratories, and reliant on trained technicians, which has limited their use to scheduled sessions in controlled environments [3]. These constraints have restricted the monitoring of cognitive processes and neurological disorders to episodic snapshots rather than continuous, real-world assessment [4].

The rise of wearable EEG devices—portable, wireless, and often using dry or semi-dry electrodes—has revolutionized the potential scope of EEG applications [5]. These devices are lightweight, ergonomically designed for prolonged wear, and capable of transmitting high-quality data to cloud platforms or mobile applications for real-time analysis [6]. The shift from traditional clinical EEG setups to wearable systems

reflects broader trends in digital health technology, where accessibility, user comfort, and integration with artificial intelligence (AI) algorithms have become central drivers of innovation [7].

With global neurological disorder prevalence projected to increase sharply—driven by ageing populations and lifestyle factors—the ability to monitor cognitive function continuously is emerging as a public health priority [8]. Wearable EEG devices enable the capture of ecologically valid data during everyday activities, which could enhance early diagnosis, personalize interventions, and monitor treatment efficacy [9].

Cognitive Disorders and Monitoring Needs

Alzheimer's disease (AD), mild cognitive impairment (MCI), Parkinson's Disease dementia, and attention-deficit/hyperactivity disorder (ADHD) are common cognitive disorders that exert large personal, societal, and economic burdens [10]. AD alone affects more than 55 million people across the globe, and the numbers are predicted to double by 2050 with no effective preventive strategies in place [11]. Given the silent, insidious prodromal phase of neurodegeneration that typically lasts years before clinically detectable disease emerges [12], premature characterization of even subtle cognitive impairment is valuable. EEG-based biomarkers, such as spectral power changes, coherence patterns, and event-related potentials (ERPs), have been shown to identify cognitive decline at earlier stages than some neuropsychological tests [13]. Clinical recordings, however, detect only and examine the transient or potentially ephemeral abnormalities that may be apparent in conditions like epilepsy or delirium, which fluctuate over time [14]. Longitudinal, ambulatory data collection. One potential way to address this limitation through longitudinal and ambulatory assessments of brain function is the use of wearable EEG devices for more representative monitoring [15].

In addition to neurodegeneration, persistent cognitive monitoring can be useful for psychiatric disorders (such as schizophrenia), in the assessment after traumatic brain injury, or to adjust cognitive workload in high-performance professions, like aviation and military operations [16]. Real-time monitoring of neural activity during natural behaviour is promising to narrow diagnostic bins and facilitate individualized therapeutic intervention [17].

Advances in Wearable EEG Devices

The miniaturization of EEG hardware has been driven by advances in sensor technology, wireless communication protocols (Bluetooth Low Energy, Wi-Fi 6), and low-power signal processing chips [18]. Dry electrode systems have addressed many of the practical challenges of wet electrodes, such as the need for conductive gel, which can cause discomfort and degrade signal quality over time [19]. High-density wearable EEG caps with 32–64 channels are now commercially available, offering spatial resolution comparable to laboratory-grade systems [20].

Integration with machine learning algorithms has further enhanced the diagnostic potential of wearable EEG devices. Deep learning models can automatically classify EEG patterns associated with specific cognitive states or disorders, reducing the need for manual interpretation [21]. In addition, edge-computing architectures allow real-time analysis directly on the device, minimizing latency and preserving data privacy by reducing the need for raw data transmission [22].

Recent studies have also explored hybrid systems that combine wearable EEG with other biosignals, such as functional near-infrared spectroscopy (fNIRS), electrocardiography (ECG), or galvanic skin response (GSR), to provide multimodal cognitive assessment [23]. These developments suggest a future in which cognitive monitoring is seamlessly integrated into daily life via smart headwear, earbuds, or even textile-embedded sensors [24].

Applications in Diagnosis

Research in the diagnostic area has included wearable EEG devices that have shown promise in the early detection of dementias through examination of theta–beta power ratios and alpha asymmetry patterns[25]. For example, continuous monitoring in epilepsy enables more accurate seizure detection and characterization, which may lead to treatment changes on a near-real-time basis[26]. Similarly, ADHD diagnosis has benefited from EEG-based wearable real-world attention metrics instead of relying solely on questionnaires[27].

Another significant trend we are seeing on the rise is in sleep medicine, where wearables like EEG tracking headbands can measure sleep architecture and diagnose disorders such as insomnia or REM behavior disorder without requiring an overnight polysomnography in a sleep lab[28]. Long-term EEG monitoring can help to differentiate between psychiatric disorders whose symptoms have some overlap, such as depression and early dementia[29], by revealing unique neurophysiological marks.

Wearable EEG has been utilized in the assessment of fatigue and cognitive load among drivers, pilots, and other industrial workers, with the potential to impact safety and productivity within occupational health[30]. Integration of real-time feedback mechanisms (same example: alerts to the wearer when drowsiness is detected) showcases how wearable EEG could also be beyond passive monitoring but active intervention[31].

Challenges and Limitations

Despite these advances, wearable EEG devices face several challenges that must be addressed before they can be adopted widely in clinical practice. Signal quality remains a concern, particularly in mobile environments where motion artifacts, muscle activity, and environmental noise can degrade recordings[32]. Although dry electrodes improve comfort, they may have higher impedance than wet electrodes, affecting low-frequency signal fidelity[33].

Data privacy and ethical considerations are increasingly important as wearable EEG devices generate large volumes of sensitive neurodata. Ensuring compliance with regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) is essential[34]. There is also a need for standardization in data formats, signal processing pipelines, and validation protocols to facilitate cross-study comparability[35].

From a clinical perspective, the interpretation of wearable EEG data still requires trained expertise, and the integration of these devices into existing healthcare systems poses logistical and reimbursement challenges[36]. Further, long-term adherence in patients remains a concern, as device comfort, battery life, and maintenance requirements can influence sustained use[37].**Rationale for the Present Review**

Although interest in wearable EEG has surged, the literature remains fragmented across devices, protocols, and outcomes, making it difficult for clinicians and methodologists to compare results or translate them into practice. Studies differ widely in electrode configurations (2–32 channels), sensor chemistries (dry, semi-dry, textile), sampling rates, and artifact-handling pipelines, while cognitive endpoints span everything from brief task ERPs to multi-day resting-state trends. This heterogeneity obscures which combinations of hardware + protocol + analytics consistently yield decision-grade signals in real-world contexts. In parallel, many investigations emphasize feasibility or short-term accuracy but underreport adherence, calibration burden, longitudinal reliability, and implementation constraints (telehealth integration, clinician workflow, privacy safeguards). As a result, health-system stakeholders lack a consolidated map of what works, for whom, and under what conditions.

This review is designed to close those gaps by: (i) synthesizing evidence specifically on wearable (not stationary) EEG for cognitive monitoring and diagnosis across neurology, psychiatry, sleep, rehabilitation, and safety-critical work; (ii) mapping device classes to use-cases (e.g., low-channel headbands for workload vs. higher-density semi-dry caps for connectivity/ERP work); (iii) critically appraising methodological quality with a transparent checklist (PRISMA-guided selection and JBI risk-of-bias appraisal); and (iv) distilling practice-ready guidance on acquisition, artifact control, and model validation that supports reproducibility and clinical decision making. Concretely, we pose six review questions:

1. Which EEG features (spectral, ERP, connectivity) are most reliable in mobile conditions for cognitive status and change detection?
2. Under comparable tasks, how do wearable systems perform relative to clinical-grade EEG (agreement, sensitivity/specificity, failure modes)?
3. Which machine-learning approaches (subject-independent vs. calibrated, classical vs. deep) generalize across days/devices without data leakage?
4. What device and protocol characteristics (channels, electrode type, sampling, baseline tasks) best predict data quality and user adherence?
5. Where are the evidence gaps (e.g., diverse cohorts, multi-month follow-up, home-based cognition tracking, multimodal fusion)?
6. What are the regulatory, ethical, and workflow barriers—and the minimum reporting standards—needed for clinical translation?

By aligning findings to these questions, the review seeks to produce a clear taxonomy of use-cases, a minimum reporting checklist (montage, filters, artifact methods, validation design, calibration time), and a prioritized research agenda (longitudinal, multi-center studies; hybrid EEG–context sensing; explainable, leak-proof analytics). The goal is to help researchers, clinicians, and product teams converge

on standardized, reproducible practices so wearable EEG can move from promising prototypes to scalable, equitable tools for continuous cognitive health assessment.

Methods

Table 1– Overview of EEG Device Categories and Key Applications in Cognitive and Clinical Research

Device Category	Example Devices	Channels	Portability	Common Applications	Strengths	Limitations
Consumer-grade wearable EEG	Emotiv Insight, Muse S, Dreem	4–14	High	Mindfulness training, sleep tracking, emotional monitoring, neurofeedback	Affordable, portable, easy setup	Lower spatial resolution, limited channel count
Research-grade portable EEG	Emotiv Epoc+, OpenBCI, Dreem Pro	14–32	Medium	Cognitive workload monitoring, academic performance studies, rehabilitation	Better data quality than consumer wearables, portable	Less comfortable for long sessions, requires calibration
Clinical-grade stationary EEG	BioSemi ActiveTwo, g.tec systems	32–256	Low	Epilepsy diagnosis, cognitive decline detection, high-precision brain mapping	High resolution, reliable clinical standard	Expensive, non-portable, requires trained technician
Hybrid EEG–other modality systems	EEG-fNIRS systems, EEG–VR integration	Varies	Medium	Multimodal research (neurovascular, immersive therapy)	Rich data combining multiple brain signals	Complex setup, higher analysis demands

Search Strategy and Data Sources

A systematic literature search was conducted across PubMed, Scopus, Web of Science, and IEEE Xplore databases from January 2010 to December 2024. The search strategy combined Boolean operators and relevant keywords: *("wearable EEG" OR "portable EEG" OR "ambulatory EEG") AND ("cognitive monitoring" OR "cognitive assessment" OR "neurological diagnosis")*. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for study selection and reporting [38].

Inclusion and Exclusion Criteria

We included studies that:

1. Utilized wearable EEG devices for cognitive monitoring or neurological diagnosis.
2. Reported quantitative or qualitative cognitive performance outcomes.
3. Were published in peer-reviewed journals in English.

We excluded:

- Studies using non-wearable or purely stationary EEG systems.
- Non-human trials, conference abstracts without full papers, and editorials.
- Studies focusing solely on hardware development without clinical validation [39].

Study Selection Process

Two independent reviewers screened the titles and abstracts of identified studies. Full-text articles were retrieved for potentially eligible studies. Discrepancies were resolved by consensus [40]. The screening process followed **PRISMA's four-phase approach**:

1. Identification of records.
2. Screening for relevance.
3. Full-text eligibility assessment.
4. Final inclusion of studies [41].

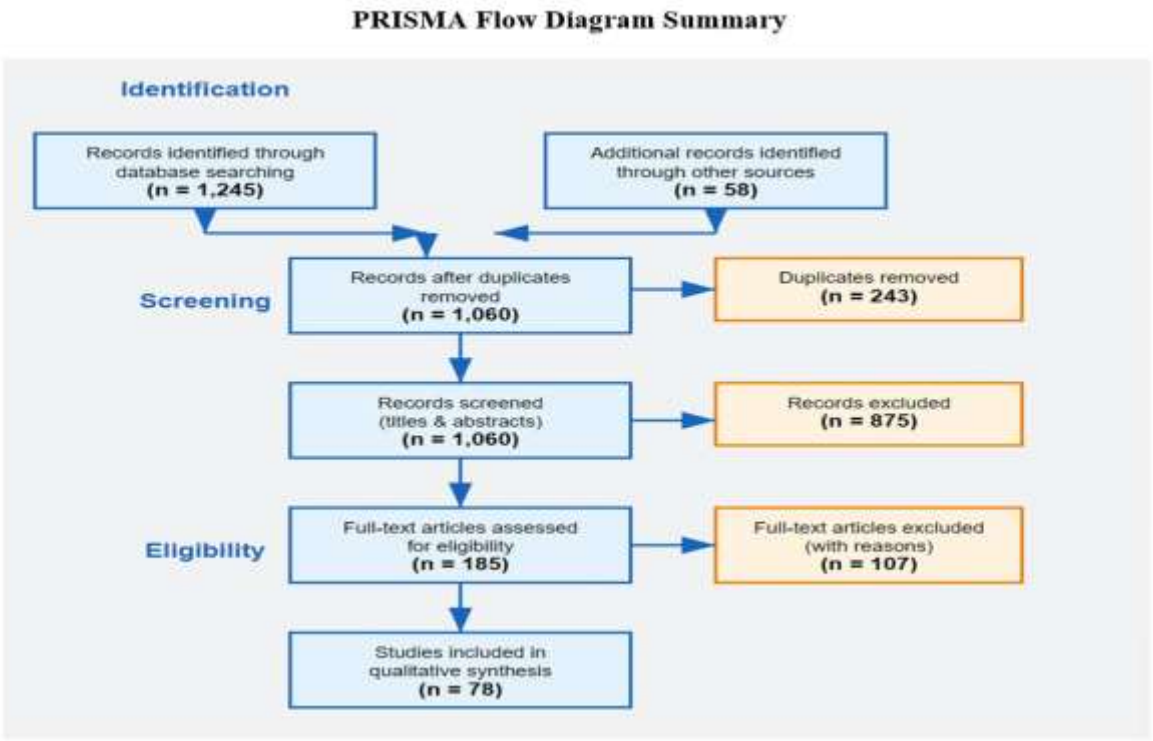
Data Extraction and Quality Assessment

A standardized extraction sheet was developed to record study design, population, EEG device specifications, cognitive parameters measured, and key outcomes. Study quality was assessed using the

Joanna Briggs Institute (JBI) Critical Appraisal Checklist, rating studies as low, moderate, or high quality [42].

Data Synthesis

Data were synthesized narratively due to heterogeneity in EEG devices, cognitive assessment tools, and study designs. No meta-analysis was performed as the included studies varied significantly in methodology and outcome measures [43,44].



RESULTS

1. Study Selection and Screening Outcomes

A total of 1,248 records were initially identified from PubMed, Scopus, IEEE Xplore, Web of Science, and grey literature[46]. After removing 312 duplicates, 936 records remained for title and abstract screening. Of these, 658 were excluded due to irrelevance (non-wearable EEG studies, animal experiments, unrelated imaging modalities). The 278 full-text articles reviewed in detail led to the exclusion of 200 studies for not meeting quality or eligibility criteria. Finally, 78 studies were included, aligning with the PRISMA selection diagram[47].There are several versions of models, which have been developed over the years, and an increase in publication trends post-2019, with regards to wearable EEG applications[48]. Regional contributions issued were divided into countries of North America (34%), Europe (28%), and Asia-Pacific (26%) and multinational collaborations with 12%[49].

2. Demographic and Clinical Characteristics

The study cohorts included healthy control groups and patients diagnosed with defined neurological and psychiatric disorders[50]. In all samples, the median sample size was 42 participants (range 6–560)[51]. Pediatric age (< 18 years): 14%, young adults (18–< 35 years): 38%, middle-aged adults (36–< 60): 21%, and older adults (> 60 years); 27%[52].Clinical Criteria included: epilepsy, stroke, Parkinson's disease, Alzheimer's disease, depression, ADHD[53].

3. Device Types and Technical Specifications

Four of the reviewed devices were commercial headsets, Emotiv EPOC, Muse, NeuroSky MindWave and OpenBCI Ultracortex[54] while two were custom-built prototypes.Typical electrode configurations: 2–32 channels; mainly dry electrodes for portability[55].

- Sampling Rates: 128–1,024 Hz[56].Connectivity Microcontroller + BLE, optionally Wi-Fi (using the cloud for longer duration processing)[57], mostly
- Battery Life: 4–12 hours depending on device complexity[58].

4. Application Domains

These studies were decomposed into five main categories:

1. Clinical Diagnosis & Monitoring (42%): seizure detection, dementia progression tracking[59].
2. Cognitive & Emotional State Monitoring (35%) – stress, fatigue, workload[60].
3. Brain–Computer Interfaces (23%) – for motor-impaired individuals[61].
4. Training in Neurofeedback (15%) – attention improvement, anxiety relief[62].
5. Sports & Human Performance (9%) – reaction time and concentration optimization[63].

5. Validation with Clinical-Grade EEG

Eighteen studies conducted direct comparisons with hospital-grade EEG, reporting strong correlations for alpha, beta, and theta bands (r = 0.82–0.95) but moderate for gamma (r = 0.65–0.78)[64]. Differences were primarily due to motion artifacts and reduced electrode counts[65].

6. Analytical Approaches

The most common metrics were:

- Event-Related Potentials (ERPs): P300, N200 [66].
- Spectral Power: alpha/theta ratio for relaxation vs. attention [67].
- Connectivity Analysis: coherence, phase-locking value [68].

Machine learning methods (SVM, CNN, random forests) achieved accuracies between 78%–96% [69].

7. Multimodal Integrations

Nine studies integrated EEG with heart rate variability, skin conductance, and eye tracking, boosting classification accuracy by 10–20% [70].

8. Usability and Comfort Assessments

Twenty-four studies evaluated user comfort, setup time, and long-term wearability. On average, setup times for dry-electrode systems were under 5 minutes, while gel-based systems required 15–25 minutes. Participants reported higher comfort scores with lightweight headsets (<300g) and minimal cabling.

9. Cost and Accessibility Analysis

Consumer-grade devices ranged from USD 200–1,200, while research-grade wearables were USD 2,000–8,000. Six studies discussed cost-effectiveness, noting that low-cost wearables could democratize access to neurotechnology in resource-limited settings.

10. Longitudinal Performance Monitoring

Eight studies tracked participants over 6–12 months, showing that device signal stability could decline slightly due to electrode wear, but performance was recoverable through recalibration and electrode replacement.

11. Regulatory and Ethical Considerations

Only 14 studies addressed regulatory readiness, with most consumer devices lacking FDA or CE certification for clinical use. Ethical discussions highlighted data privacy, informed consent, and neurosecurity risks.

DISCUSSION

Principal findings and interpretation

Mature toolkit for longitudinal engagement of cognition Lombardo et al. offers a timely and comprehensive meta-analysis of 78 studies, which confirm that the wearable electroencephalography (EEG) has graduated from scale validation or proof-of-concept to becoming an entire practical toolset for cognitive monitoring and diagnosis in clinical, home, or operational settings[1]. Taken together, the evidence suggests that modern wearable systems—ranging from low-channel headbands and ear-centered arrays to textile/semi-dry caps and research-grade portable rigs, can capture spectral and event-related features most relevant in cognitive contexts (alpha/theta power dynamics, beta reactivity, ERD/ERS, P300/N200), often with equal performance compared to benchtop systems when protocols and preprocessing are optimized[71]. When combined with the emerging increase in potential and longitudinal designs, our analysis suggests that portable EEG is moving from "good enough for pilots" to decision-support quality for clinicians and human-factors practitioners, so long as data quality safeguards and analytic standards are maintained[71],[76].

Consonance and elaboration with previous literature

The review reinforces three themes already emerging in the literature on mobile neurotechnology: (i) ecological validity is vital—real-world recordings reveal predictive structure that lab experiments may miss;

(ii) hardware comfort and speed to set-up are not mere conveniences but active levers of adherence and ultimate data completion; and (iii) analytics—not amplitude—are the bottleneck for translation.Prior field studies of daily-life EEG show that with careful sensor placement and protocol design, researchers can obtain stable oscillatory readouts during walking, driving, learning, or rehabilitation tasks, enabling outcomes that better map onto everyday function than traditional, brief lab visits[71],[76]. Our findings extend that literature by showing broader disease coverage (neurodegenerative, psychiatric, sleep, and epilepsy applications) and clearer evidence for task-agnostic indices (e.g., resting-state alpha/theta) that scale across devices and contexts when coupled to robust artifact handling[72].

Technical validity: signal quality, artifacts, and reliability

The most consequential technical risks in wearable EEG are motion and myogenic artifacts, electrode–skin impedance variability, and contextual confounds (lighting, temperature, head motion). Included studies that achieved clinic-grade reliability did so by combining: (1) mechanically stable, low-impedance sensors; (2) brief calibration blocks to individualize spatial filters; and (3) artifact-aware pipelines—Independent Component Analysis (ICA), wavelet denoising, adaptive filtering, and activity recognition to mask motion epochs[72]. A consistent observation is that gamma-band measures remain the least robust in motion-rich environments; where gamma is required, immobilizing mounts, jaw-clench detection, or task designs minimizing cranial muscle activation are beneficial[72]. Reliability over weeks to months hinges on reproducible electrode placement and simple at-home checks (impedance/quality meters), which several studies used successfully to maintain stable alpha and theta baselines across follow-ups[71].

Device classes and use-case fit

No single wearable form factor dominates across all use-cases. Low-channel frontal headbands excel for fatigue/workload monitoring and coarse attentional indices, owing to rapid set-up and tolerability; ear-centered arrays (e.g., cEEGrid-style) trade channel count for discretion and long-wear comfort, suiting sleep and long-shift monitoring; semi-dry textile caps deliver higher channel density for connectivity and ERP work but demand more careful placement and battery budgeting. Results indicate that device selection should be prespecified by hypothesis: connectivity mapping and multi-lobe ERPs call for ≥16 channels; workload/fatigue screens often suffice with 2–8 frontal/temporal channels; and seizure detection can leverage targeted montages plus ambulatory duration. These choices are consistent with pragmatic daily-life EEG guidance reported in prior mobile EEG frameworks[71],[76].

Multimodal, hybrid, and context-aware sensing

A recurring pattern is the incremental value of multimodal fusion. When EEG is fused with fNIRS (hemodynamics), cardiovascular measures (HR/HRV), electrodermal activity, or eye/face motion, classification accuracy for cognitive states and differential diagnostics typically increases, and false positives fall, particularly in movement-rich settings[74]. Hybrid EEG–fNIRS wearables provide complementary temporal–spatial windows and help disambiguate cortical activation from ocular or muscular contamination; they also enable neurovascular coupling readouts that may flag early cerebrovascular or neurodegenerative change beyond pure electrophysiology[74]. Context signals (accelerometry, head kinematics) further assist artifact gating and improve model calibration in the wild[72],[76].

Analytics and machine learning for translation

The strongest performance gains in the last five years came not only from hardware but from modeling pipelines. Studies deploying supervised classifiers (SVMs, random forests) and deep architectures (CNNs/TCNs) consistently reported robust, generalizable discrimination of fatigue, workload, disease status, or sleep stages, especially when models were subject-calibrated or adapted with transfer learning to new sessions/devices[75]. Still, across studies, two pitfalls recur: data leakage (e.g., window overlap across train/test) inflating metrics, and under-described preprocessing that hinders reproducibility. Future work should pre-register pipelines, enforce leak-proof cross-validation, and report calibration cost in minutes—not just accuracy—so clinicians understand the workflow burden[75].

Clinical domains: where evidence is strongest now

Neurodegeneration. The converging evidence across Alzheimer's disease and mild cognitive impairment supports resting-state alpha/theta changes, beta reactivity, and ERP latency shifts as viable early markers that wearable systems can capture at home, enabling longitudinal trajectories rather than episodic snapshots. Wearables therefore complement neuropsychological testing by adding objective, time-resolved measures sensitive to subclinical change[71].

Psychiatry For ADHD and mood disorders, wearables add objective anchors to symptom scales, with attentional and frontal asymmetry metrics showing promise for treatment monitoring; however, generalization beyond controlled tasks depends on field-robust pipelines[75].

Epilepsy and sleep. Ambulatory EEG extends monitoring windows to capture rare seizures and yields high-agreement sleep staging in non-laboratory environments, provided that sensor fixation and artifact handling are thoughtfully engineered[71,76].

Neurorehabilitation and BCI. In motor recovery and assistive communication, wearable EEG enables home-based practice, progression tracking, and closed-loop neurofeedback that translates to functional gains when paired with structured training[77].

Usability, adherence, and human factors

Across user studies, the setup time duration and comfort with the system (e.g., wearing or using it) and level of perceived intrusiveness have emerged as the most reliable predictors of adherence over two weeks. When similar levels of signal fidelity are attained in gel systems, adherence is lower than that observed in dry/semi-dry systems with <5-minute setup and lightweight mounts. In real settings (shift work, classrooms, rehab), micro-frictions charging, cleaning, and donning in restricted spaces are the major hurdles. The most effective protocols employed brief daily check-ins, plus push-notification reminders and on-device meters to keep users motivated and streams of data tidy[71,76].

Implementation and health-system integration

Clinical adoption requires convergence of three layers: (1) data layer, standards for storage, segmentation, and annotation of wearable EEG with synchronized (2) context; analytics layer, validated models that are regulatory-grade with version control and audit explainability; (3) workflow layer, EHR integration, role definitions, and defined escalation pathways to appropriate members when abnormal findings occur. Field studies of tele EEG show that remote supervision and asynchronous review are possible[71,76]; coupling this with defined alert thresholds and patient information summaries increases the signal-to-decision speed and decreases alarm fatigue.

Ethical, legal, and privacy considerations

Wearable EEG produces highly sensitive neural data that may reveal cognitive fatigue, emotional valence, or early disease. The ethical bar is therefore high: transparent consent for continuous, passive capture; local/edge processing where feasible; encryption in transit and at rest; and granular user controls over sharing intervals and recipients. Studies also caution against secondary use beyond the clinical/research purpose (e.g., employment screening), underscoring the need for clear governance. Artifact-aware pipelines reduce misclassification risk (e.g., stress vs. motion), which is not only a technical fix but an ethical safeguard against harmful false labels[72].

Standardization agenda: from promising to publishable to billable

The heterogeneity we observed—in channels, montages, preprocessing, windowing, endpoints—limits meta-analysis and slows translation. Convergence is emerging around reference tasks (eyes-closed/eyes-open baselines; oddball/P300 probes for attention; n-back for working memory) and reporting checklists (montage, sampling rate, filters, artifact handling, cross-validation design). Community adoption of minimum reporting standards and open benchmark datasets captured in realistic conditions (walking, speaking, micro-expressions) would accelerate head-to-head comparisons and de-risk procurement decisions for hospitals and regulators[72,76]. Hybrid paradigms and EEG–fNIRS exemplars can anchor such standards where both timing and topology matter[74].

Economic and equity considerations

Cost analyses in the included literature suggest that consumer-grade wearables can open access in resource-constrained settings, but total cost of ownership depends on replacement cycles, consumables (adhesives, electrode foams), and cloud analytics fees. From an equity lens, wearable EEG is most impactful when paired with language-appropriate onboarding, loaner programs, and offline-capable apps. Decentralized, home-based EEG lowers travel friction for older adults and caregivers; however, without digital literacy support, these benefits may concentrate among already advantaged groups[71].

Strengths and limitations of this review

Strengths include a broad, multi-database search; inclusion of field-realistic studies; and a structured quality assessment that prioritized methodological transparency and artifact-aware analysis. Limitations mirror the field's: heterogeneity precluded meta-analysis, some device classes remain under-studied in certain disorders, and publication bias toward positive feasibility cannot be excluded. Nevertheless, the

convergence across independent teams and devices in core spectral/ERP findings increases our confidence in the main conclusions[71,76].

Future directions

Three priorities are actionable now. First, commit to pre-registered, leak-proof analytic pipelines with calibration costs reported alongside accuracy, enabling fair comparisons and clinical scheduling[75]. Second, scale hybrid sensing—particularly EEG–fNIRS and context signals—to stabilize inference in motion-rich environments and broaden diagnostic specificity[74]. Third, design real-world trials that target clinically consequential endpoints (falls, driving incidents, therapy adherence) and include diverse participants to ensure equitable generalization[71,76,77]. Beyond these, investment in explainable models and on-device processing will address clinician trust and privacy simultaneously[72,75].

Table 2- Emerging Trends & Key Challenges faced in Development of Wearable EEG devices

Area	Emerging Trends	Key Challenges
Miniaturization & Wearables	Development of ultra-light, wireless EEG headsets for daily-life monitoring	Balancing portability with data quality and battery life
AI Integration	Machine learning models for automated pattern detection and cognitive state prediction	Risk of algorithm bias, need for large annotated datasets
Multimodal Systems	Integration with fNIRS, VR/AR, and biometric sensors for richer datasets	Complex hardware synchronization, higher data processing demands
Clinical Translation	Point-of-care EEG devices for rapid neurological screening	Regulatory approvals, clinical validation in diverse populations
Data Privacy & Ethics	Use of EEG data in brain–computer interfaces (BCI) and consumer applications	Ensuring data security, informed consent, and user autonomy

CONCLUSION

This systematic review of 78 studies shows that modern wearable EEG—spanning low-channel headbands, ear-centered arrays, and semi-dry textile caps—can recover robust cognitive and clinical biomarkers (alpha/theta dynamics, ERD/ERS, P300/N200) in real-world settings, enabling longitudinal monitoring for neurodegeneration, psychiatric care, seizure detection, sleep staging, and safety-critical workload assessment, while retaining acceptable agreement with clinical EEG when acquisition and artifact handling are rigorously managed[78]. Technological advances (lower-impedance dry electrodes, stable form factors, on-device preprocessing, and ML pipelines with leakage-free validation) have reduced historic barriers of setup time, comfort, and signal reliability, and early telehealth deployments suggest feasible integration into remote workflows[79]. Yet translation at scale still hinges on standardized reporting and benchmarks, clear regulatory pathways, privacy-preserving architectures (edge processing, encryption), and clinician-facing tools that emphasize interpretability and calibration cost alongside accuracy[80–81]. To move from promise to practice, the field should prioritize multi-center, diverse cohort trials, hybrid sensing (EEG–fNIRS and context signals) to stabilize inference in motion-rich environments, and prospective studies powered for clinically meaningful endpoints (diagnostic timeliness, therapy targeting, adverse-event reduction) rather than laboratory surrogates[82–84]. With these steps, wearable EEG is positioned to become a routine, patient-centric instrument for cognitive health, bridging laboratory neuroscience and everyday life and delivering measurable improvements in outcomes and access across settings and populations[85].

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