Low-Cost Wearable EEG in Non-Medical HCI: A Systematic Review of Applications, ML Pipelines, and Deployment Challenges

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Abstract. Consumer-grade and portable electroencephalography (EEG) devices have enabled broader adoption of brain-sensing technologies in non-medical human–computer interaction (HCI), supporting interactive applications beyond traditional laboratory and clinical settings. However, the literature remains fragmented across domains, device settings, and machine learning pipelines, making it difficult to compare methods and assess real-world feasibility. This paper presents a PRISMA-guided systematic review of recent studies on low-cost and wearable EEG in non-medical HCI. We synthesize the most common application domains, including interactive control and gaming, affective computing, workload and user experience evaluation, and emerging XR/VR-related contexts. We further analyze end-to-end EEG–ML pipelines, covering acquisition protocols, preprocessing and artifact handling, representation learning trends, and evaluation practices, highlighting the ongoing methodological shift from traditional feature-based approaches toward deep learning and attention-based models (including Transformer-style architectures). Finally, we summarize recurring technical and human-centered challenges reported in the literature, including noise and motion artifacts, limited generalization, reproducibility gaps, usability and comfort constraints, and privacy and consent considerations. Based on these findings, we provide actionable best-practice recommendations to support more transparent reporting, stronger evaluation, and robust deployment of consumer EEG-enabled HCI systems.

Keywords: consumer-grade EEG · wearable EEG · low-cost EEG · human–computer interaction · deep learning · brain–computer interface · systematic review

1 Introduction

Consumer-grade and portable EEG technologies have rapidly evolved from specialized neurotechnology into practical sensing tools for HCI research. In recent years, low-cost headsets such as Muse, Emotiv, NeuroSky, and OpenBCI—together with increasingly portable dry-electrode systems—have made it possible to collect neural signals beyond clinical and tightly controlled laboratory settings. As a result, EEG is now being explored across a wide range of non-medical interactive contexts, including interactive control and gaming, affective computing, attention and engagement monitoring, neuroadaptive learning, and cognitive workload evaluation. These developments increasingly intersect with Extended Reality (XR) and spatial computing, where real-time user-state inference can enable more adaptive, immersive, and personalized experiences. In parallel, a growing body of recent work has explored EEG-enabled interactive systems using consumer-grade or portable devices, including EEG-controlled gameplay and motor imagery interfaces, real-time personalization pipelines, and practical end-to-end EEG–ML system design considerations [45, 1, 46, 32, 8, 52, 49].

Despite this rapid progress, the research landscape remains difficult to compare and build upon. Studies frequently adopt different devices, recording setups, preprocessing pipelines, and evaluation protocols. While performance metrics (e.g., accuracy and F1-score) are commonly reported, critical human-centered factors—such as comfort, usability, accessibility, and privacy—are not consistently discussed. This fragmentation makes it difficult to determine what findings are transferable across application domains and what technical and design practices are necessary to build robust EEG-enabled interactive systems for real-world deployment.

To address these gaps, this paper presents a PRISMA-guided systematic review of studies that use consumer-grade and portable EEG for machine learning–driven, non-medical HCI applications. Rather than only summarizing reported decoding performance, we synthesize evidence across the full pipeline—from EEG hardware choices and experimental paradigms, to preprocessing and artifact handling, to modeling decisions (including deep learning and emerging Transformer/attention-based methods), and finally to evaluation practices and human-centered outcomes. This review also aims to connect technical progress with actionable design implications: we examine not only which approaches are most common, but also where current systems break down in real-world use (e.g., robustness to noise and motion artifacts, cross-user generalization, usability and comfort constraints, and reproducibility of reported results). Based on these findings, we propose an integrated framework that organizes the literature into actionable design and implementation considerations for future EEG-enabled interactive systems, including emerging XR/spatial computing scenarios.

Research Questions.

- RQ1 (Application Domains): What non-medical HCI application domains most frequently use consumer-grade and portable EEG (e.g., gaming/BCI interaction, affective computing, workload/UX evaluation, and emerging XR/VR contexts), and what interaction goals do these systems support?
- RQ2 (Methodologies and ML Pipeline): What end-to-end EEG–ML pipelines are commonly adopted in this literature (acquisition protocols, preprocessing/artifact handling, feature or representation learning, and evaluation setup), and how are model families distributed (traditional ML, deep learning, Transformer- and attention-based, and hybrid approaches)?
- RQ3 (Challenges and Evaluation Considerations): What recurring technical and human-centered challenges are reported (e.g., noise/artifacts, generalization, reproducibility, usability/comfort, privacy and consent), and what evaluation practices are used to assess real-world feasibility and user-centered deployment?

Table 1. Prior reviews vs. this review (summary).

Ref.	**Focus**	**Main gap**
[42]	General BCI survey	Not HCI-specific
[39]	Consumer EEG sensors	Limited deployment focus
[37]	Consumer EEG research	Limited pipeline synthesis
[12]	Wearable EEG systems	Limited HCI feasibility metrics”
[43]	Consumer EEG + games	Narrow domain
[47]	MI directional control	Narrow task focus
[40]	Consent practices in HCI	Not EEG-specific
[17]	Risks of BCI use	Limited HCI design guidance
This review	Non-medical HCI + EEG–ML	Integrated framework

2 Related Work

2.1 Reviews of Consumer-Grade EEG in Non-Medical HCI

Recent systematic reviews and scoping analyses have documented the rapid expansion of consumer-grade EEG research across non-medical HCI domains. Värbu et al. [42] provide a broad review of EEG-based BCI research from 2009 to 2019, highlighting the widespread adoption of accessible headsets such as Emotiv EPOC and NeuroSky MindWave for applications including emotion recognition, attention monitoring, and fatigue detection. Subsequent reviews similarly describe a gradual shift away from laboratory-grade EEG systems toward more portable and deployable setups, often coupled with hybrid AI–EEG approaches better suited for real-world interaction contexts [37, 13, 51].

Alongside this shift, usability and multimodal interaction considerations have received increasing attention. Several surveys emphasize that deployment feasibility, user comfort, and integration with other sensing modalities are becoming as important as classification accuracy in consumer EEG studies [37, 54, 27, 26, 30, 33, 34]. This trend is particularly evident in emerging work that situates EEG within immersive VR and XR environments, where real-time interaction and user experience constraints play a central role [23]. Related research has also examined low-cost EEG headsets in applied settings such as drowsiness detection, drawing attention to practical limitations related to signal reliability, wearability, and long-term use outside controlled laboratory environments [21].

Beyond application coverage, recent work has critically examined how EEG studies are conducted and reported within HCI. Putze et al. [29] analyze experimental practices and reporting challenges in HCI studies using brain signals, highlighting barriers to reproducibility, reuse, and cross-study comparison. Complementing this perspective, Kosch et al. [19] survey methods for measuring cognitive workload in HCI, providing broader context for understanding how EEG-based workload assessment fits within established evaluation practices. More broadly, informed consent, transparency, and responsible human-subject research practices are increasingly emphasized as the community scales up physiological and brain-sensing studies [40]. In addition, emerging best-practice efforts such as PhysioCHI highlight open science workflows, documentation standards, and reproducibility guidance for integrating physiological signals into HCI systems research [5]. From a risk and governance perspective, systematic analyses further identify recurring concerns in BCI research, including privacy, autonomy, security, and informed consent [17], as well as ethical challenges driven by commercialization and consumer deployment contexts [9].

In addition to gaming-oriented BCIs, consumer and portable EEG have been explored for broader non-medical HCI goals such as cognitive state detection and learning-related user-state inference. For example, EEG has been used to distinguish interaction modalities under the same task demand (e.g., writing vs. typing), to identify attention lapses such as daydreaming, and to support learning analytics and personalized feedback systems [35, 44, 36, 31].

2.2 Device Evolution and Practical Wearability

Beyond application-oriented surveys, device-centered reviews help explain why consumer and portable EEG systems have become increasingly viable for interactive systems research. Sawangjai et al. [39] review consumer-grade EEG sensors as research tools and summarize key strengths and limitations that affect data quality, including electrode configuration, noise susceptibility, and ease of setup. More recently, He et al. [12] survey the diversity and suitability of wearable and wireless EEG systems, providing a comparative perspective on portability, design trade-offs, and intended use cases.

Although some wearable EEG reviews focus primarily on medical applications, they nevertheless offer useful insights into hardware maturity and user-facing constraints that also carry over to non-medical HCI contexts [50, 3]. Complementary evaluation studies further assess consumer-device fidelity and accessibility in practice, highlighting variability in signal quality and usability across devices [22]. Beyond hardware capabilities alone, several studies emphasize the importance of systematically evaluating usability and user experience when deploying consumer EEG devices. Cano et al. [4] demonstrate that low-cost EEG signals can support coarse-grained assessment of user experience, while Gaspar-Figueiredo et al. [10] report findings from a replication study on measuring user experience in adaptive interfaces using EEG, underscoring ongoing challenges related to reliability and consistency. Arias-Cabarcos et al. [2] further examine trade-offs between performance, user burden, and practical deployment in EEG-based authentication systems. Looking forward, emerging form factors such as ear-EEG have been proposed as promising directions to improve comfort and social acceptability for everyday use, while maintaining sufficient signal quality for interactive applications [14].

2.3 Interactive Control and Gaming as Testbeds

Gaming has long served as an influential testbed for consumer EEG research, in part because it naturally supports closed-loop interaction and repeated user engagement under realistic constraints. Vasiljevic et al. [43] present a systematic literature review of BCI games based on consumer-grade EEG devices, documenting a wide range of interaction paradigms and evaluation practices. Similarly, Xie et al. [47] review consumer and portable EEG applications for directional game control via motor imagery, reinforcing the relevance of gaming-oriented HCI scenarios for studying real-time feasibility, calibration effort, and user experience requirements. More recent surveys further reflect growing interest in neurotechnology-enabled gaming, including visual evoked potential (VEP)–based BCI approaches, which expand the range of interaction techniques explored in entertainment contexts [15]. In parallel, emerging work emphasizes the need for user-centric evaluation protocols that assess not only decoding performance but also real-world usability in immersive AR/XR contexts [7].

Beyond survey-level evidence, recent research has increasingly focused on practical EEG-controlled game implementations and evaluation of real-time feasibility. Work on motor imagery controllers and consumer-grade EEG gameplay systems highlights key HCI considerations such as calibration burden, robustness to noise, feedback loop design, and personalization for usability [45, 8, 32].

Overall, gaming-oriented studies should be interpreted as one representative HCI domain among several, but they remain valuable for evaluating closed-loop interaction, real-time constraints, and user experience considerations under realistic usage conditions.

2.4 Methodological Shifts in EEG–ML Pipelines

From a methodological perspective, prior work frequently compares traditional classifiers such as SVM and LDA with deep learning approaches including CNNs, DNNs, and hybrid models [6, 38]. While deep models often report improved predictive performance, many studies also note persistent sensitivity to artifacts, noise, and subject variability, particularly in consumer-grade acquisition settings. These challenges have motivated increasing interest in strategies such as transfer learning and domain adaptation to improve generalization and enable personalization in real-world HCI systems. Recent neuroadaptive XR systems further demonstrate the feasibility of using real-time EEG feedback to support attention enhancement and workload reduction in immersive environments [20].

More recent work has increasingly adopted attention mechanisms and Transformer-based architectures to explicitly model spatial and temporal dependencies in EEG signals. Attention-based convolutional and Transformer models have reported improved performance in emotion recognition by learning channel-wise and temporal importance patterns [11, 48]. Related studies further demonstrate that self-attention mechanisms may enhance EEG representation learning by capturing inter-channel relationships and long-range temporal dynamics [41, 25]. These modeling strategies are particularly well suited to consumer-grade EEG, where signal nonstationarity and noise make robust representation learning critical for downstream HCI tasks such as affective computing and user-state estimation.

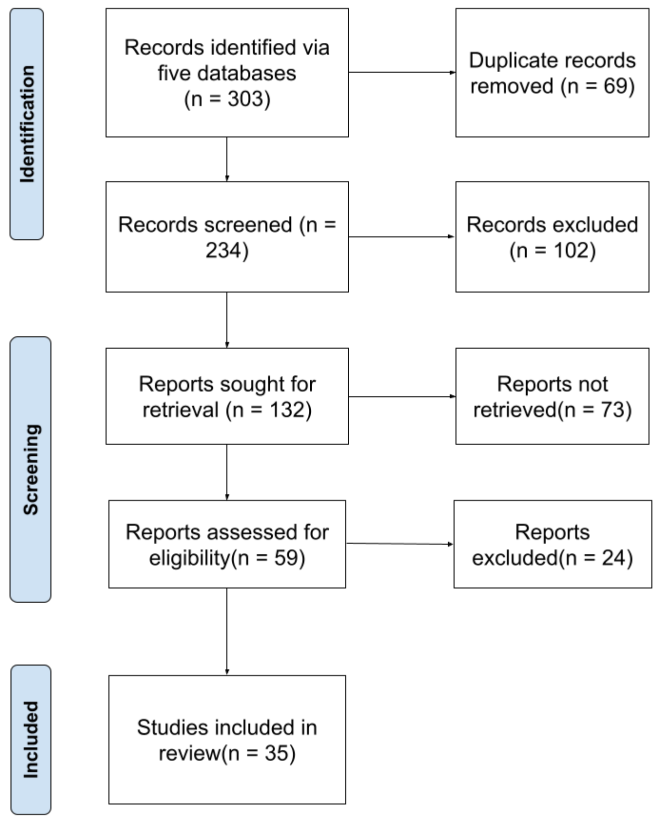

Fig. 1. PRISMA flow diagram summarizing the literature selection process.

This shift is also reflected in recent attention-based and Transformer-hybrid EEG modeling studies and review efforts, which emphasize improved spatial–temporal representation learning and robustness under noisy or low-channel acquisition settings [18, 53, 49].

3 Method

This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [28] to ensure methodological transparency and reproducibility. A structured literature search was conducted across five databases—Google Scholar, IEEE Xplore, PubMed, ACM Digital Library, and Web of Science—using Boolean combinations of key concepts related to low-cost and wearable EEG devices,

Table 2. Inclusion and exclusion criteria applied during PRISMA screening for studies using consumer-grade EEG in non-medical HCI applications.

Inclusion / Exclusion Criteria	Include?
Employs consumer-grade or portable EEG devices (e.g., Muse, Emotiv, OpenBCI, NeuroSky) in non-medical interactive or HCI-relevant contexts	Yes
Uses machine learning / deep learning for classification, prediction, or adaptive feedback (including neuroadaptive systems)	Yes
Addresses HCI application domains such as affective computing, gaming, attention/engagement monitoring, or cognitive workload assessment	Yes
Reports sufficient methodological details (EEG device, protocol, model/evaluation) to support transparency and interpretation	Yes
Includes usability, accessibility, reproducibility/reporting practices, or ethical/privacy discussion relevant to EEG-enabled interactive systems	Yes
Written in English and published as peer-reviewed journal or full-length conference paper (2015–2026)	Yes
Focuses on clinical diagnosis, medical rehabilitation, invasive EEG/neuroimaging, or clinical treatment outcomes as the primary objective	No
Lacks EEG hardware description, study design clarity, or sufficient reproducibility/reporting detail	No

non-medical HCI applications, and machine learning–based analysis. The search targeted peer-reviewed publications between 2015 and 2026.

Studies were screened according to the inclusion and exclusion criteria summarized in Table 2. In total, 303 records were identified across the selected databases. After removing duplicates ($n = 69$), 234 records remained for title and abstract screening, of which 102 were excluded. The remaining 132 reports were sought for retrieval, and 59 full-text articles were successfully assessed for eligibility after excluding non-retrieved reports ($n = 73$). Following full-text screening, 35 studies were included in the final synthesis. The complete selection process is summarized in the PRISMA flow diagram in Figure 1.

For each included study, we coded key technical and human-centered dimensions, including EEG device type, application domain, acquisition protocol, preprocessing and artifact handling, feature/representation learning strategy, machine learning model family, and evaluation metrics. In addition to predictive performance (e.g., accuracy and F1-score), we recorded qualitative factors relevant to HCI deployment such as reported

Table 3. Keyword groups and qualitative frequency in the PRISMA search strategy for consumer-grade EEG studies in non-medical HCI.

Category	Example keywords	Freq.
Consumer EEG Devices	Muse; Emotiv; OpenBCI; NeuroSky; low-cost EEG; wearable EEG headset	H
Application Domains	affective computing; adaptive gaming; attention tracking; cognitive workload; engagement; neuroadaptive interface	H
Immersive Interaction	VR; AR; XR; extended reality; spatial computing; immersive interface	M
Machine Learning	SVM; LDA; CNN; RNN; transformer; deep learning; hybrid model; domain adaptation	M–H
Signal Processing	band-power; filtering; ICA; artifact removal; feature extraction; preprocessing pipeline	M
Human-Centered Evaluation	usability; comfort; accessibility; user experience; real-world evaluation; protocol	M
Ethics & Governance	informed consent; privacy; ethics; neuroprivacy; trust; risk	M
Performance Metrics	accuracy; F1-score; precision; recall; cross-subject evaluation; generalization	M

usability and comfort, accessibility considerations, study reporting completeness, and privacy/ethics implications.

4 Results

This section reports findings from the PRISMA-included literature, organized by the three research questions. Following HCII conventions, results are presented as descriptive patterns across application domains (RQ1), methodological and modeling choices (RQ2), and recurring challenges and evaluation considerations (RQ3). Summary distributions are provided in Tables 4–7, with Table 6 highlighting a focused subset of empirical EEG-based UX evaluation studies.

RQ1 (Application Domains). Across the included set, consumer-grade and portable EEG research in non-medical HCI spans several recurring application clusters (Table 4). Prominently represented domains include immersive XR/VR-oriented interaction and evaluation [27], gaming and BCI control paradigms [38], and affective computing tasks such as emotion recognition [48]. In addition to application-driven studies, a substantial portion of the literature is review- or survey-oriented, synthesizing research trends, devices, and methodological practices to support more systematic development in the field [37, 51, 54]. Device-focused work further contextualizes feasibility constraints by emphasizing portability and wearability trends, which influence long-term adoption and deployment in everyday settings [50, 39].

RQ2 (Methodologies and ML Pipeline). Methodological patterns reported in the included papers emphasize end-to-end pipeline design rather than model choice alone (Table 5). Traditional machine learning approaches remain common, reflecting the continued use of feature-based baselines and interpretable pipelines in consumer EEG set-

Table 4. RQ1 summary (application domains and study themes) based on included studies.

Domain	Typical goal (3–5 keywords)	Example papers
XR / VR EEG interaction	hands-free control; adaptation; immersive feedback	[27]
Gaming / BCI control	real-time control; engagement; feedback loop	[38]
Affective computing / emotion	emotion decoding; affective HCI; state modeling	[48]
Meta / research landscape	domain mapping; devices used; trends	[37, 51]
Wearable EEG devices (context)	wearability; portability; device evolution	[50]
Reproducibility / reporting	experiment reporting; transparency; reuse	[29]
Consumer EEG adoption	device usage; research categories; validation	[39, 54]

tings [39]. Deep learning is frequently reported as a dominant methodological trend in recent consumer EEG work, often motivated by the need for representation learning under noisy and low-channel acquisition conditions [38, 51]. Transformer and attention-based modeling appears explicitly in recent EEG decoding work, particularly for modeling temporal dependencies and channel-wise relevance [48]. In parallel, survey and best-practice papers highlight that methodological rigor depends on acquisition stability, preprocessing transparency, and evaluation consistency, supporting the need for standardized EEG–ML reporting practices in non-medical HCI research [29, 54].

Table 5. RQ2 summary (methodology and ML lens) from included studies.

Model group	What it emphasizes (3–5 keywords)	Example papers
Traditional ML	feature extraction; baseline pipelines; comparability	[39]
Deep Learning	representation learning; robustness; classification gains	[38, 51]
Transformer & attention	multi-dim attention; channel weighting; temporal deps	[48]
Hybrid architectures	CNN-based encoders; fusion; multi-stage pipelines	[48, 51]
Pipeline / method standards	reporting structure; dataset metadata; reproducibility	[29, 54]

RQ3 (Challenges, Evaluation, and Design Guidance). Across the included studies, the most consistently reported challenges relate to deployment feasibility, evaluation

Table 6. Empirical evidence for EEG-based UX / adaptive interface evaluation (subset).

Ref.	Setting	Result keywords
[4]	UX assessment	low-cost EEG; UX feasible
[10]	Adaptive UI (replication)	EEG UX metrics; replication

completeness, and reproducibility (Table 7). Several papers emphasize that heterogeneous reporting practices and incomplete methodological descriptions limit reuse and cross-study comparison, particularly in HCI contexts where experimental design varies substantially across tasks and settings [29]. Usability and multimodal evaluation gaps are repeatedly observed, reflecting that performance reporting alone is insufficient for consumer-facing deployments [54, 37]. For XR/VR-integrated BCI systems, the literature highlights additional constraints such as comfort, integration complexity, and safety considerations in immersive interaction settings [27]. Device limitations, including electrode stability, noise susceptibility, and form-factor constraints, remain common factors affecting reliability and generalization in consumer-grade EEG acquisition [39, 50, 38]. Empirical UX-oriented evidence, though less consistently reported, demonstrates practical feasibility for using EEG signals as evaluation cues in adaptive interface and UX assessment scenarios [4, 10].

Table 7. RQ3 summary (challenges, evaluation, ethics, and reproducibility) reported in included studies

Paper	Risk / ethics dimension	Main concern (3–5 keywords)	Suggested mitigation
[29]	reproducibility; transparency	missing details; heterogeneity; reuse barrier	reporting checklist; reuse guidance
[54]	usability; multimodal evaluation	deployment gaps; limited validation	HCI evaluation; multimodal protocols
[27]	XR usability; deployment validity	integration issues; safety/comfort limits	system evaluation; multimodal BCI
[37]	usability; adoption	device constraints; feasibility gaps	system-level metrics; UX reporting
[39]	device reliability	noise; electrodes; fidelity limits	device-aware interpretation
[38]	generalization; maturity	uncontrolled envs; benchmark gaps	datasets; standardized pipelines
[50]	wearability; practicality	comfort limits; form factor constraints	wearable design; long-term use
[48]	model interpretability (weak)	attention reliance; evaluation scope	ablation; robust evaluation
[51]	methodological drift	inconsistent protocols; comparability	taxonomy; unified benchmarks

Summary of Key Findings. Overall, the included literature indicates that non-medical consumer EEG research in HCI is concentrated in a small set of application areas, most notably XR/VR interaction and evaluation, gaming-oriented BCI control, and affective computing [27, 38, 48]. Methodologically, the field exhibits a clear shift toward deep and attention-based modeling while maintaining feature-based baselines in low-cost settings [39, 38, 48]. Finally, reproducibility, usability reporting, and device reliability constraints are recurrent cross-cutting themes, motivating the need for standardized protocols that integrate technical performance reporting with human-centered evaluation measures [29, 54, 37].

5 Discussion

This review synthesized 35 PRISMA-included studies on consumer-grade and portable EEG for non-medical HCI applications, with emphasis on application domains (RQ1), methodology and modeling pipelines (RQ2), and recurring challenges affecting real-world feasibility (RQ3). While the Results section summarized descriptive patterns across domains and model families (Tables 4–7), the goal of this Discussion is to interpret what these patterns imply for future research and for building robust EEG-enabled interactive systems. In particular, we highlight (i) why attention-based and hybrid architectures appear increasingly effective in consumer EEG settings, (ii) how EEG-enabled HCI is being shaped by XR/spatial computing constraints, and (iii) what practical best practices can be recommended based on cross-study evidence and common failure modes.

5.1 Interpreting the shift toward deep and Transformer-based models

A consistent trend across the reviewed literature is the methodological shift from traditional classifiers (e.g., SVM/LDA with hand-crafted features) toward deep learning and attention-based architectures (Table 5). This shift is not simply a reflection of broader AI trends; rather, it aligns with several structural characteristics of consumer-grade EEG data and HCI deployment contexts.

First, consumer EEG signals are often low-channel, noisy, and non-stationary due to device form-factor constraints (e.g., dry electrodes, wireless headsets, variable placement and impedance). In such settings, representation learning becomes a practical advantage: deep models can learn task-relevant patterns directly from raw or minimally processed signals, reducing dependence on hand-crafted features that may not generalize well across devices or contexts. Second, attention mechanisms and Transformer-based architectures offer a principled way to model both temporal dependencies and channel-wise relevance, which is particularly important when signal quality varies over time and across sensors. For example, attention can focus on informative segments of an EEG window while down-weighting noisy intervals or unreliable channels, yielding more robust decoding under real-world conditions.

Third, in many HCI scenarios, the primary objective is not offline accuracy alone but robust, repeatable decoding under imperfect conditions (e.g., user movement, multitasking, and limited calibration). Hybrid architectures that combine convolutional encoders with attention layers can capture local EEG structure (e.g., frequency-specific patterns) while still supporting long-range temporal modeling and flexible weighting. Therefore, the emerging evidence suggests that Transformer-based and hybrid architectures may be outperforming classical SVM pipelines in this context because they better match the underlying data properties and the robustness constraints of deployable interactive systems.

At the same time, the review indicates that this trend should be interpreted cautiously. Across the included studies, benchmarking practices remain heterogeneous, and deep models can be sensitive to evaluation design. In particular, within-subject evaluation may overestimate real-world performance, and reporting often lacks enough detail to fully assess generalization and calibration burden. For this reason, deep learning and attention-based models should be encouraged, but not treated as universally superior without stronger evaluation consistency and cross-user validation (Table 7).

Recent hybrid EEG architectures combining convolutional encoders with attention/Transformer modules further support this direction, suggesting that flexible spatial–temporal weighting can improve representation learning and downstream robustness in real-time EEG-enabled HCI settings [53, 18, 49, 24].

5.2 Implications for XR and spatial computing

One of the most important emerging developments in this research area is the growing intersection between consumer EEG and XR/spatial computing systems (Table 4). XR environments amplify both the opportunities and the practical constraints of EEG-based interaction. On the opportunity side, immersive environments provide rich closed-loop contexts where EEG can support adaptive feedback, engagement measurement, workload-aware interfaces, and affective personalization. On the constraint side, XR introduces additional motion artifacts, comfort requirements, latency sensitivity, and safety considerations. These constraints make EEG deployment more complex than in traditional desktop or seated laboratory settings.

This also motivates multimodal pipelines that combine EEG with complementary sensing such as eye tracking, where recent Transformer-based multi-task models suggest promising directions for stable attention and gaze inference in interactive systems [24, 16].

From an HCI systems perspective, XR-driven adoption emphasizes the need to treat EEG not as an isolated classifier input, but as one component within an integrated interactive pipeline. This includes (i) headset and device selection matched to motion and comfort constraints, (ii) artifact-aware preprocessing strategies that explicitly account for movement-related noise, and (iii) evaluation protocols that go beyond performance reporting to include usability and user burden. The reviewed literature also suggests that XR scenarios may benefit disproportionately from multimodal sensing (e.g., EEG combined with eye tracking or other physiological signals), because redundancy across modalities can stabilize inference when one signal source becomes unreliable. Therefore, XR/spatial computing is not merely an additional application domain; it is likely to be a driver that shapes best practices for consumer EEG deployment across HCI more broadly.

Table 8. Recommended best practices for low-cost and wearable EEG in non-medical HCI systems (interpretive synthesis).

Pipeline stage	Best practice	Rationale and supporting evidence
Study design & tasks	Use task paradigms aligned with the target interaction (e.g., affect, workload, or control) and report task timing clearly	HCI EEG studies remain difficult to compare due to heterogeneous protocols; clearer design reporting improves reuse and cross-study interpretation [29].
Device selection	Match headset choice to interaction constraints (channels, electrode type, wear time, mobility) and explicitly discuss trade-offs	Consumer-grade devices vary in fidelity and wearability; device-aware interpretation is necessary for robust conclusions [39, 12].
Acquisition setup	Standardize sampling rate, reference, montage, and environmental conditions; report headset placement and calibration time	Signal quality is sensitive to electrode stability and setup variability, especially outside controlled laboratory settings [22, 39].
Preprocessing & artifact handling	Use transparent preprocessing (filter bands, epoching, artifact strategy) and consider motion artifacts for XR/VR scenarios	Noise and motion artifacts are persistent barriers in real-world deployment; XR adds additional artifact sources [27, 29].
Modeling strategy	Prefer deep learning / attention-based models when data scale allows; keep traditional ML baselines for comparability	Recent literature shows increasing shift from SVM/LDA to deep and Transformer-based architectures, potentially due to improved representation learning under noise[48, 38].
Evaluation protocol	Include cross-subject evaluation or domain shift testing; report calibration burden and real-time constraints when relevant	Many systems fail in generalization and real-world feasibility; evaluation beyond within-subject accuracy is critical [54, 29, 45, 1].
Human-centered outcomes	Measure usability, comfort, and user experience alongside performance; report dropouts and user burden	Performance-only reporting is insufficient for HCI adoption; usability evidence remains inconsistent across studies [37, 10].
Reproducibility & reporting	Use reporting checklists, share code when possible, and include complete dataset/protocol metadata	Incomplete reporting limits reproducibility and reuse; stronger documentation is emphasized in HCI brain-signal research [29, 5].
Ethics & privacy	Include consent practices and discuss neuroprivacy risks, especially for consumer deployments	Consumer neurotechnology raises privacy and autonomy risks; ethical reporting is increasingly required in HCI [17, 40].

5.3 Best practices and actionable guidance for EEG-enabled HCI systems

A key outcome of this review is the identification of recurring technical and human-centered barriers that limit reproducibility and deployment feasibility, including incomplete reporting, inconsistent evaluation protocols, device reliability constraints, and limited usability/comfort assessment (Table 7). These issues collectively explain why the field remains fragmented despite rapid growth. To address these gaps, we synthesize a set of recommended best practices across the end-to-end pipeline, summarized in Table 8. Rather than proposing a new algorithm, this table provides practical guidance intended to improve comparability, reuse, and robustness of EEG-enabled interactive systems.

Several themes in Table 8 warrant emphasis. First, methodological transparency is a prerequisite for scientific progress in this space: authors should consistently report acquisition protocols, headset placement, calibration duration, filtering/epoching details, and artifact-handling methods. Second, evaluation should be aligned with intended deployment. If a system is intended for consumer use, studies should report cross-user generalization, calibration burden, and real-time constraints. Third, HCI outcomes must be treated as first-class evidence, not secondary to decoding performance. Usability, comfort, dropout rates, and user burden should be reported alongside accuracy and F1-score, especially for long-duration or immersive applications.

Finally, the results also suggest that ethics and privacy considerations are not optional for consumer neurotechnology; they are central to responsible deployment. As EEG moves toward everyday settings, neuroprivacy concerns, consent practices, and risk mitigation should be explicitly discussed, particularly when systems attempt to infer affective or cognitive states.

5.4 Limitations

This review has several limitations. First, despite the PRISMA-guided screening process, the included literature remains heterogeneous in terms of tasks, devices, and evaluation metrics, which limits quantitative comparison across studies. Second, while this work covers papers published between 2015 and 2026, the research landscape is rapidly evolving, and newly emerging XR-integrated systems may not yet be fully represented. Third, because many papers do not report complete methodological details, the synthesis may be influenced by reporting bias, where better-documented studies are more likely to be included and interpreted.

5.5 Future work

Future research should prioritize stronger benchmarking and reproducibility standards for consumer EEG in HCI. This includes shared datasets that reflect realistic consumer constraints, standardized evaluation protocols emphasizing cross-user generalization, and reporting checklists that capture both technical pipeline details and human-centered outcomes. In addition, XR and spatial computing represent a high-impact direction where EEG-enabled systems can deliver practical value, but only if developers address motion artifacts, comfort, and ethical concerns in real deployment contexts. More broadly, the field would benefit from designing systems that integrate EEG into multimodal pipelines and from adopting evaluation frameworks that jointly measure performance, usability, and real-world feasibility (Table 8).

6 Conclusion

This PRISMA-guided systematic review synthesized 35 studies (2015–2026) on low-cost and wearable EEG in non-medical HCI, with emphasis on end-to-end machine learning pipelines and real-world feasibility. Overall, the literature demonstrates rapid growth and broadening adoption, but remains fragmented in methodology, reporting practices, and evaluation rigor.

For RQ1 (Application Domains), low-cost wearable EEG research in HCI commonly appears in application areas such as gaming and BCI control, affective computing, and cognitive workload/UX evaluation, with increasing intersection with XR/VR and spatial computing. Across these domains, EEG is primarily used to support hands-free interaction, user-state inference, neuroadaptive feedback, and experience-aware personalization. For RQ2 (Methodologies and ML Pipeline), included studies commonly follow a pipeline of device-specific acquisition, preprocessing and artifact handling, feature extraction or representation learning, and supervised classification and evaluation. A clear methodological shift is observed from traditional ML pipelines (e.g., SVM/LDA with hand-crafted features) toward deep learning and attention-based models (including Transformer-style architectures), including hybrid approaches. For RQ3 (Challenges and Evaluation Considerations), recurring barriers include noise and motion artifacts, limited cross-user generalization, inconsistent reporting and reproducibility, and under-reporting of usability and comfort outcomes, alongside growing concerns related to consent, privacy, and neuroethical risks in consumer deployment contexts.

Based on these findings, progress in EEG-enabled HCI should be evaluated not only by decoding performance but also by deployment readiness, user burden, and ethical responsibility. The recommended best practices summarized in Table 8 provide actionable guidance to strengthen methodological transparency, evaluation validity, and human-centered feasibility for future EEG-enabled interactive systems, including emerging XR/spatial computing scenarios.

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