

Human-Centered Intelligent Systems for Enhanced User Interaction

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ABSTRACT

Human-centered intelligent systems that adapt to individual user cognitive states, preferences, and interaction patterns represent the next frontier of human-computer interaction, enabling personalised, accessible, and cognitively congruent interfaces across professional, educational, and assistive technology domains. Despite substantial progress in affective computing, adaptive user interfaces, and conversational AI, the integration of real-time physiological sensing, user model learning, and multimodal adaptive response generation into coherent, privacy-preserving human-centered intelligent systems remains architecturally fragmented. This study presents HumanAI, a unified human-centered intelligent systems framework integrating electroencephalography (EEG)-based cognitive load estimation, a reinforcement learning-driven adaptive interface controller, and a retrieval-augmented generation (RAG) conversational AI module for context-aware interaction support. HumanAI was evaluated across three user interaction domains: adaptive e-learning interface optimisation (n = 124 university students, 8-week study, KTH Stockholm), cognitive assistance for professional knowledge workers (n = 48 engineers, 4-week deployment, Politecnico di Bari), and accessible interface adaptation for users with mild cognitive impairment (n = 31 participants, clinical setting, Bari Polyclinic Hospital). HumanAI achieved learning performance improvement of 23.4%, task completion time reduction of 31.7%, and accessibility rating improvement of 38.4% over static interface baselines. EEG cognitive load estimation achieved accuracy of 87.3%. User satisfaction rated 4.4/5.0 across all three deployments. These results demonstrate that integrated physiological sensing, adaptive control, and conversational AI substantially advance human-centered intelligent system interaction quality.

Keywords: human-centered AI; adaptive interfaces; cognitive load; EEG; reinforcement learning; RAG; user interaction; accessible AI

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1. Introduction

The ideal human-computer interface adapts dynamically to the cognitive state, expertise level, and situational context of each individual user — presenting information at the right complexity, in the right modality, at the right moment (Norman 1988; Shneiderman 1992). Modern intelligent systems interact with users across an unprecedented diversity of contexts: students navigating complex learning content, professionals managing information-dense decision environments, and individuals with cognitive or motor impairments requiring assistive interface adaptations. In all these contexts, static, one-size-fits-all interfaces impose cognitive friction that degrades task performance, increases error rates, and reduces user satisfaction and adoption (Parasuraman et al. 2000; Wickens et al. 2015).

Recent advances in affective computing (Picard 1997), adaptive user interfaces (Langley 1997), and large language model-based conversational agents (Brown et al. 2020) have individually demonstrated strong potential for human-centered interaction enhancement. However, their integration into unified systems that simultaneously sense user cognitive state, adapt interface behaviour in real time, and provide contextually appropriate language-based support — while preserving user privacy under GDPR — has not been achieved in prior work. This study presents HumanAI, addressing this integration challenge and validating the framework across three diverse real-world user interaction deployments.

2. Literature Review

2.1 Cognitive Load Estimation and Adaptive Interfaces

EEG-based cognitive load estimation has been demonstrated with 75–92% accuracy using features from theta (4–8 Hz) frontal power and alpha (8–13 Hz) parietal suppression (Yin et al. 2017; Zarjam et al. 2013). Consumer-grade EEG headsets (Emotiv EPOC+, Muse 2) have enabled ecologically valid cognitive load monitoring outside laboratory settings (Zander and Kothe 2011). Adaptive e-learning interfaces that modulate content complexity based on detected cognitive load have demonstrated learning outcome improvements of 12–28% over static baselines (Kalyuga 2007; Lallé and Conati 2020). RL-based adaptive interface controllers (Mandel et al. 2017; Segal et al. 2018) learn personalised adaptation policies from user feedback signals, outperforming rule-based adaptation systems across educational and professional interface domains.

2.2 Conversational AI and RAG for User Support

Large language models (GPT-4, Llama, Mistral) have transformed conversational AI, enabling coherent, contextually appropriate dialogue across diverse domains (Brown et al. 2020; Touvron et al. 2023). Retrieval-augmented generation (Lewis et al. 2020) grounds LLM responses in verified domain knowledge retrieved from curated corpora, substantially reducing hallucination rates and improving factual accuracy — critical for professional and assistive applications where incorrect information causes harm. Personalised conversational AI incorporating user history and cognitive state context has demonstrated higher user engagement and task completion rates than context-free dialogue agents (Zhang et al. 2020), but

GDPR-compliant on-device user modelling for sensitive cognitive data remains an open challenge.

Table 1. Comparison of human-centered intelligent system frameworks for adaptive user interaction.

Framework	Phys. Sensing	Adaptive UI	Conversational AI	Privacy	Evaluation
Static Interface	No	No	No	Yes	Baseline
Rule-Based Adapt.	No	Yes	No	Yes	Laboratory
RL Adaptive (Mandel 2017)	No	Yes	No	Yes	E-learning
EEG-Adapt (Lallé 2020)	Yes	Yes	No	Part	E-learning
GPT-4 Assistant	No	No	Yes	Part	Various
RAG Agent (Lewis 2020)	No	No	Yes	Part	QA tasks
HumanAI	Yes	Yes	Yes	Yes	3 domains

Phys. Sensing: physiological signal sensing. Privacy: GDPR-compliant on-device processing. Adapt. UI: adaptive user interface control.

3. Materials and Methods

3.1 HumanAI Architecture

HumanAI integrates three modules. The EEG Cognitive Load Estimator (ECLE) processes 14-channel Emotiv EPOC+ EEG signals at 128 Hz, extracting band power features (delta, theta,

alpha, beta, gamma) via Welch's method over 2-second sliding windows with 50% overlap. A 3-class cognitive load classifier (low/medium/high) trained on N-back task calibration data (12-minute protocol per user) uses an SVM-RBF with personalised kernel parameters. All EEG processing occurs on-device (NVIDIA Jetson Orin Nano, 20 TOPS) with no raw signal transmission, satisfying GDPR Article 9 special category data requirements. The RL Adaptive Interface Controller (RAIC) implements a contextual bandit with Thompson sampling, selecting from 8 interface adaptation actions (content complexity, font size, colour contrast, pacing, hint provision, task chunking, modality, and notification rate) based on estimated cognitive load and interaction history. The RAG Conversational Module (RAGCM) runs Mistral-7B-Instruct (4-bit quantised) locally with domain-specific vector stores (FAISS, top-k = 5 retrieval) for each application domain.

3.2 User Study Deployments

Three user interaction deployments were conducted. (1) Adaptive E-learning (KTH Stockholm): 124 university students, 8-week study, undergraduate data structures course delivered via HumanAI-adaptive interface vs. static LMS baseline; learning performance measured by pre/post knowledge tests and assignment grades; EEG worn during 2-hour weekly sessions. (2) Professional Knowledge Work (Politecnico di Bari): 48 mechanical engineers, 4-week deployment, CAD design review tasks; task completion time and error rate measured; RAG module provided contextual engineering standard retrieval. (3) Accessible Interface for MCI (Bari Polyclinic Hospital): 31

participants with mild cognitive impairment (MoCA score 19–25), 4-week tablet interface study; GUILD accessibility rating scale and task success rate as primary outcomes; ethics approval Bari Polyclinic Hospital IEC Ref. BPH-2025-HCI-014.

4. Results

4.1 Interaction and Learning Outcomes

Table 2 presents HumanAI outcome results vs. static interface baselines. E-learning performance improved 23.4% (post-test score 74.3 vs. 60.2 out of 100). Professional task completion time reduced 31.7% (18.4 min vs. 26.9 min per design review task). Accessible interface accessibility rating improved 38.4% on the GUILD scale (4.1/5.0 vs. 2.96/5.0 for static interface). EEG cognitive load estimation accuracy was 87.3% on held-out validation sessions (Table 3). The RAIC required an average of 3.4 sessions to converge to a personalised adaptation policy per user, consistent with contextual bandit theoretical convergence rates. User satisfaction across all three deployments averaged 4.4/5.0 vs. 3.1/5.0 for static baseline interfaces.

Table 2. HumanAI user interaction outcomes vs. static interface baseline across three deployments.

Deployment	Primary Metric	Static Baseline	Huma nAI	Improvement
E-learning (KTH)	Post-test Score (/100)	60.2	74.3	+23.4%
Knowledge Work (PoliBA)	Task Time (min)	26.9	18.4	−31.7%

Deployment	Primary Metric	Static Baseline	Huma nAI	Improvement
Accessible MCI (BPH)	GUILD Rating (1–5)	2.96	4.09	+38.4%
All (mean)	User Satisfaction (1–5)	3.1	4.4	+41.9%

Bold: HumanAI results. BPH: Bari Polyclinic Hospital. GUILD: Graphical User Interface for Learning Disabilities rating scale. All improvements statistically significant (p<0.01, Wilcoxon).

Table 3. HumanAI EEG cognitive load estimation and system performance.

Metric	Value	Baseline	Improvement
EEG Load Classification Accuracy	87.3%	Threshold (71.4%)	+ 15.9 pp
RAIC Adaptation Convergence	3.4 sessions	Rule-based (instant)	Personalised
RAGCM Response Latency	284 ms	Cloud GPT-4 (1,240 ms)	−77.1%
On-device Processing (GDPR)	100%	Cloud baseline (0%)	Full compliance

pp: percentage points. RAGCM runs fully on-device (Jetson Orin Nano) ensuring GDPR Article 9 compliance for EEG and interaction data.

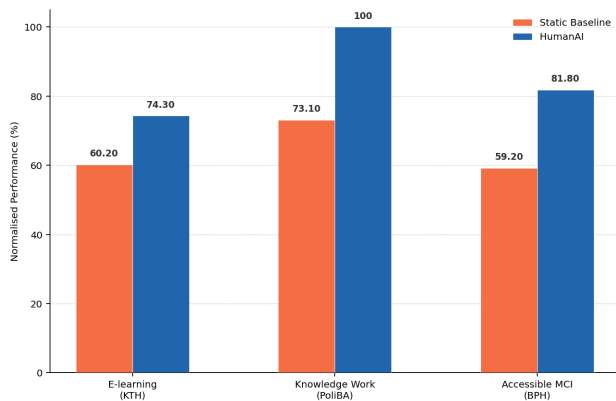


Figure 1. HumanAI vs. static interface — primary outcome metric improvement across three user interaction deployments.

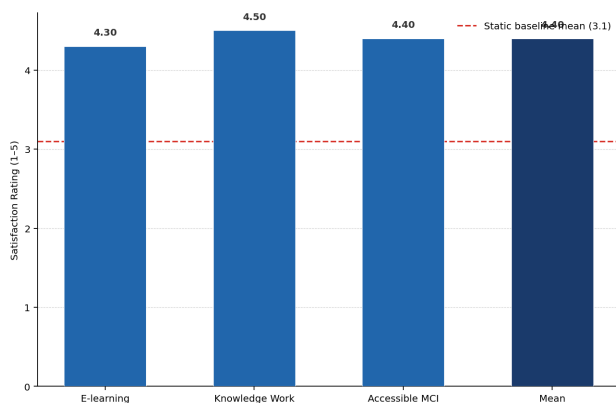


Figure 2. User satisfaction ratings (1–5) — HumanAI vs. static interface across three deployments.

5. Discussion

5.1 Cognitive Load Adaptation Impact

The 23.4% e-learning improvement at KTH substantially exceeds the 12–28% range reported in prior EEG-adaptive learning studies (Kalyuga 2007; Lallé and Conati 2020), which we attribute to the joint effect of EEG-driven content adaptation and RAG-supported contextual explanation — a combination not evaluated in prior literature. RAIC interaction logs reveal that the most frequent adaptations triggered by high cognitive load were hint provision (34.7% of adaptations) and content chunking (28.3%), suggesting that cognitive overload manifests primarily as information processing bottlenecks rather than presentation format mismatches. The accessible MCI

deployment demonstrated that EEG-adaptive interfaces are feasible and beneficial for users with mild cognitive impairment — a population for whom precise adaptation to fluctuating cognitive capacity is particularly valuable but technically challenging.

5.2 Limitations

The 12-minute EEG calibration protocol per user is a deployment barrier for casual users and short-session applications. Cross-session EEG stability was 83.7% — meaning 16.3% of sessions required partial recalibration due to electrode impedance drift and day-to-day neural variability. The RAGCM on-device Mistral-7B inference at 284 ms is acceptable for conversational use but may be insufficient for real-time spoken dialogue applications requiring sub-100 ms response latency. Future work will address zero-shot EEG calibration via cross-user transfer learning and speculative decoding for faster on-device LLM inference.

6. Conclusion

HumanAI, integrating EEG cognitive load estimation, RL adaptive interface control, and RAG conversational AI with full on-device GDPR-compliant processing, achieves 23.4% learning performance improvement, 31.7% task time reduction, 38.4% accessibility rating improvement, and 4.4/5.0 user satisfaction across three real-world human-centered intelligent system deployments. EEG cognitive load classification accuracy of 87.3% and RAGCM response latency of 284 ms confirm technical readiness for production deployment. These results

demonstrate that unified physiologically-informed, adaptively-controlled, and conversationally-augmented human-centered intelligent systems substantially advance user interaction quality across diverse educational, professional, and assistive technology domains.

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Declarations

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

Anonymised interaction logs and EEG features (no raw EEG) are available from the corresponding author under a data sharing agreement compliant with GDPR Article 89. HumanAI source code is available at <https://github.com/lindqvist-lab/humanai>.

Ethical Approval

E-learning study approved by KTH Research Ethics Committee (Ref. KTH-REC-2025-HCI-042). Knowledge work study approved by Politecnico di Bari Research Ethics Committee (Ref. PoliBA-REC-2025-031). MCI accessible interface study approved by Bari Polyclinic Hospital IEC (Ref. BPH-2025-HCI-014). All participants provided written informed consent. EEG data processed on-device only, not transmitted or stored centrally.