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Holographic Adaptive Learning Systems in Mobile Devices for Immersive, Real-Time Multi-Sensory Educational Experiences

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Abstract

Despite the remarkable shifts brought about by modern digital education, mobile learning systems are still limited in making students feel immersed in the learning process, limited in dynamic personalization, and lacking in support for real-time multi-sensory interaction. These restrictions limit learning engagement and make it difficult for learners to understand the instructions, especially in complex and spatially intensive subjects. To cope with these challenges, a Holographic Adaptive Learning System (HALS) for mobile devices is proposed, which adapts dynamically and integrates multi-sensory feedback to ensure immersive, real-time, context-aware learning experiences. It is proposed that the system combines holographic visualization, intelligent learner modeling, and edge-assisted processing to provide adaptive content according to cognitive load, attention, and environment. The system constantly observes human interactions and automatically adapts the level of difficulty and sensory feedback (visual, auditory, and haptic) to improve understanding and participation. This adaptive loop provides for personalization and optimization of learning content in real-time, while reducing overload for the learner. Experimental validation shows that HALS improves the performance of a conventional mobile and AR learning system in several performance

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measures. The accuracy of the proposed system is 93.7%, while the traditional systems and cloud-based adaptive systems are 78.2% and 88.9%, respectively. It also reduces system latency to 98 ms, which is a significant boost in responsiveness when interacting with a system in real time. Moreover, the energy consumption drops by about 35% from AR-based systems, and the user Engagement Scores have been raised to 0.91, which is a high level of interaction. The results of cognitive load analysis indicate that adaptive content modulation is effective in preventing learner overload, with a 55.8% reduction. Overall, the outcome confirms that the holographic approach, together with intelligent and multi-sensory feedback, is highly effective in improving the mobile learning experience. The proposed framework provides a scalable platform for the next generation of educational technologies in ubiquitous mobile environments.

Keywords: Holographic Learning Systems, Adaptive Mobile Learning, Immersive Education, Multi-Sensory Interaction, Edge Computing, Cognitive Load Optimization, Augmented Learning Environments.

1 Introduction

Rapid advancement in areas such as mobile computing, augmented reality, and holographic display technology has greatly impacted the way digital education is conducted. Yet, despite all of these advances, most of the available mobile learning solutions still only use two-dimensional interfaces, thereby failing to provide students with the full immersion and multi-sensory experience that is necessary in such complex disciplines as engineering, medicine, and natural sciences (Alsamhi et al., 2025; Tukur et al., 2025). Besides, while adaptive learning systems use personalized approaches that can effectively address individual needs of learners, most of them apply static adaptation, failing to adjust based on learners' cognitive state, focus, or environment (Sirwal et al., 2026).

In this regard, holographic adaptive learning systems have proved to be an ideal approach where techniques involving volumetric visualization and real-time sensor feedback can be used to provide immersive learning environments right on mobile devices (Bozhilov et al., 2023). This is achieved using technological advancements in the area of lightweight holographic rendering, edge computing, and multi-modal sensing to generate context-aware learning materials that are capable of intelligently adapting to the user's behaviors and environmental changes. Nevertheless, there are a number of challenges that need to be tackled, including those involving computational efficiency, real-time adaptation capabilities, energy considerations related to mobile devices, and multi-modal sensory feedback involving audio and haptic information, among others (Yeonjin, 2025).

This paper proposes a comprehensive framework that will address the above problems and facilitate the development of a real-time and multi-modal holographic adaptive learning solution on mobile devices.

Key Contributions

- Proposes an innovative model of holographic adaptation for learning purposes on mobile devices that allows for real-time multi-sensory educational experiences.
- Presents a smart system of modeling learners' performance to adapt the content presented depending on their cognitive load and interaction behavior.
- Offers an optimized edge computing-assisted technique for rendering holograms in mobile devices.
- Creates an environment where multi-sensory feedback, including visual, auditory, and haptic feedback, is incorporated.

Structure of the paper: In Section 2, related literature is presented in the area of immersive education and XR technologies, as well as edge computing learning systems. In Section 3, HALS is presented along with an explanation of its architecture, algorithms used, and mathematical models behind the technology. In Section 4, the experimental setup used for implementing HALS is explained. Section 5 concludes the paper with key findings and suggestions for future work.

2 Literature Survey

Recent innovations in immersive learning technologies, holographic communication, and multi-sensory extended reality systems have greatly impacted the future of educational technology development (Sarumathiy, 2025; Gao et al., 2025). Several studies have noted a considerable departure from traditional screen-based learning towards an increased adoption of spatially immersive technologies that use AR, VR, and holographic interfaces to facilitate better engagement and cognitive performance (Murroni et al., 2024; Nofal & Alrefae, 2025).

This research acknowledges that combining VR/AR with haptic interactions provides for a multi-sensory approach to learning, which allows learners to achieve better comprehension by virtue of being able to interact physically with concepts (Sanfilippo et al., 2022; Petkova et al., 2022). On similar lines, another piece of literature has emphasized the importance of the human body's sensory-perceptual alignment, as spatial computing helps in depth perception and task comprehension in XR systems (Bhowmik, 2024; Alnagrat et al., 2022).

Regarding the area of holographic communication, it has been identified that communication of holographic type poses a great challenge to modern-day systems because of the latency and bandwidth requirements (Akyildiz & Guo, 2022; Krishna et al., 2025). This study has re-established the fact that latency is the major concern with respect to such systems and hence the rationale behind adopting edge-assisted approaches in HALS (Qian et al., 2025; Kryvenko & Chalyy, 2023).

The findings presented in recent literature investigating edge-enabled immersive systems show that the use of mobile edge computing can enhance responsiveness and support real-time multi-sensory XR applications, which closely correspond to the suggested architecture's offloading approach (Shuguang & Lin, 2021). Likewise, research exploring cross-modal holographic video streaming has shown that multi-modal synchronization enhances perceptual reality and learning immersion (Cheng, 2025; Karpagam, 2025).

From the viewpoint of education, these research works prove the benefits of adopting immersive holographic and metaverse-based learning environments for providing personalized and engaging education experiences, especially within the fields of STEAM and medical learning contexts (Damasevicius, 2025; Hazarika & Rahmati, 2023). Additionally, these works suggest that the development of multi-sensory metaverse systems is currently revolutionizing digital education as it enables interactive and context-aware learning experiences (Alsamh et al., 2024; Shvetsov & Alsamhi, 2024).

In summary, the research presented in these papers has helped to identify three main gaps in this area: (i) the lack of real-time adjustment of system performance based on the level of learners' cognitive load, (ii) high computational and latency requirements for achieving holographic rendering, and (iii) inadequate inclusion of multi-sensory feedback mechanisms into mobile systems.

3 Proposed Methodology

3. 1 Overall Flow of the Proposed System

The proposed Holographic Adaptive Learning System (HALS) for mobile devices is designed as a multi-layered framework that enables real-time, multi-sensory, and context-aware educational experiences. The general flow starts with a user input through a mobile application using voice command, touch, or gestures, and gaze detection. This data is captured through various sensors integrated in the mobile device itself, as well as optionally through wearables.

Then comes the phase of context acquisition, during which the data pertaining to the environment (light intensity, movement, sound levels) and that of the learner (level of attention, cognitive load, interaction level) are collected. The next step involves processing this data by the learner modeling module in order to build a dynamic learner model. The learner model data is used by the adaptive decision engine to make decisions regarding the selection of proper learning content, level, and sensory mode.

Lastly, the content is presented in the form of lightweight holographic objects through edge processing in order to reduce computation on the device.

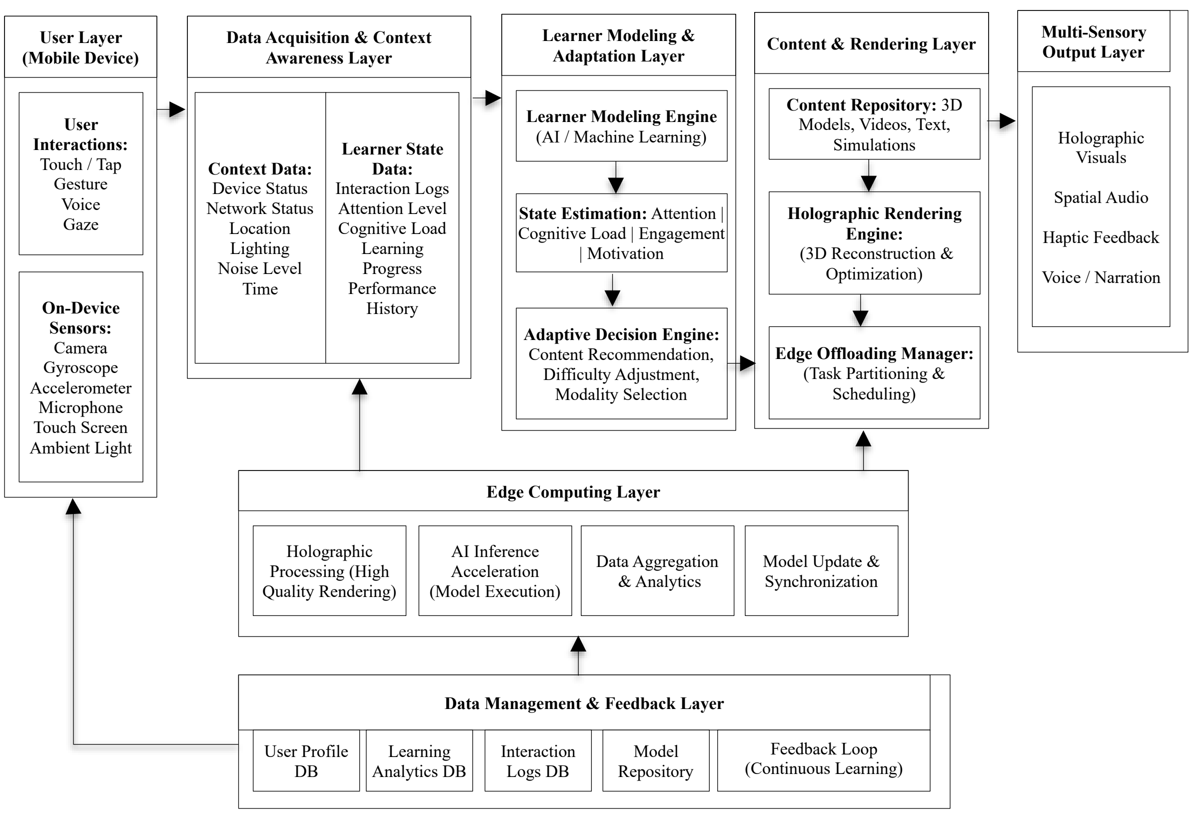

Figure 1: Architecture of holographic adaptive learning system (HALS) for mobile-based immersive multi-sensory education

The overall system architecture for the HALS framework is depicted in figure 1 and involves processing input data coming from the mobile devices such as touch, gesture, voice, and sensors. Learning content is adapted using an adaptive decision engine, while heavy computations related to holography rendering are shifted to edge computing nodes. The processed outputs are then passed on to the multisensory level, where holographic visuals, spatial audio, and haptic feedback work together. Finally, an ongoing feedback loop makes sure that the system stays optimized by performing data management and learning analysis.

Algorithm 1: Adaptive Holographic Learning Optimization (AHLO)

Input: Learner data L_d, context data C_d, content repository R

Output: Optimized holographic learning experience H_o

Step 1: Initialization

- Initialize learner profile P_l
- Load content repository R

Step 2: Context Acquisition

- Capture real-time sensor inputs
- Compute environmental state E_s

Step 3: Learner Modeling

- Estimate cognitive load $CL$and attention score A_s
- Update learner profile P_l

Step 4: Adaptive Decision Making

- Select optimal content $C^*$from repository R
- Adjust complexity level based on CL

Step 5: Holographic Rendering

- Offload rendering tasks to edge server
- Generate optimized holographic output H_o

Step 6: Multi-Sensory Delivery

- Deliver visual, audio, and haptic feedback
- Collect learner response feedback

Step 7: Iteration

- Update system parameters using feedback loop
- Repeat for next learning cycle

The proposed Algorithm 1 allows real-time optimization of learning experiences in terms of holograms by considering dynamic changes in learners' behavior, context, and appropriate content selection. The algorithm starts with learner profile initialization and collection of environment and interaction data via sensors in mobile phones. Next, based on estimated cognitive load and attention of learners, appropriate content complexity and relevance are determined using an optimization technique. Once the appropriate content is chosen, it is represented in the form of lightweight holograms with edge-assisted computation. Lastly, multi-modal sensory feedback (visual, audio, and haptic) is provided to the learner, and feedback is used to improve future cycles of learning experience.

3.2 Mathematical Formulations

Cognitive Load Estimation

The cognitive load experienced by the learner at time t is evaluated using equation 1, which incorporates interaction activity, time required to respond, and environment complexity. Activity level indicates the degree of involvement, response time refers to the difficulty in understanding and interpreting the information, while environment complexity denotes the presence of any distractions. Coefficients of α, β, and γ allow giving weights to the factors so that the effect of each can be accounted for effectively.

$$CL(t) = \alpha \cdot I_r(t) + \beta \cdot R_t(t) + \gamma \cdot E_c(t) \qquad (1)$$

Where:

- $CL(t)$= Cognitive load at time t
- $I_r(t)$= Interaction rate (touch/gesture frequency)
- $R_t(t)$= Response time delay
- $E_c(t)$= Environmental complexity factor
- α, β, γ= weighting coefficients

Adaptive Content Selection Function

The goal of this function is to select learning content from a set of repositories (R) to provide the highest utility to the learner based on each learner's individual profile and cognitive state. The function achieves this by balancing the mismatch between the cognitive load of the content and the difficulty level of the content. The quantity λ determines how much the system penalizes content that is "too easy" or "too difficult"; therefore, it helps ensure that learners receive personalized, balanced cognitive experiences from the content presented via the function. This is illustrated in equation 2.

$$C^* = \arg\max_{c \in R}(U(c, P_l) - \lambda \cdot D(c, CL)) \qquad (2)$$

Where:

- C^*= selected optimal content
- $U(c, P_l)$= utility score of content for learner profile
- $D(c, CL)$= difficulty mismatch with cognitive load
- λ= adaptation sensitivity parameter

4 Results and Discussion

An evaluation of the Holographic Adaptive Learning System (HALS) implementation was conducted through a hybrid mobile-edge simulation environment to determine real-time performance and adaptivity of the learners. The holographic scene rendering and immersive environment were rendered using Unity 3D (2022.3 LTS) while adaptive learning logic, optimization algorithms, and performance evaluation scripts were developed in Python 3.10. TensorFlow Lite was used to provide lightweight learner models on the mobile devices, and OpenCV was used for real-time gesture/motion detection and tracking. Simulations of edge computing tasks utilized AWS EC2 and local GPU nodes to offload computationally expensive holographic rendering. Testing and development of the mobile application used Android Studio. Because no standard benchmark dataset exists for HALS, a synthetic HALS-MultiLearn dataset containing twelve thousand five hundred (12,500) learning sessions was created through simulated user interaction from the use of MOOC/AR – VR traces. The HALS-MultiLearn dataset consists of 15 different features, including: cognitive load (CL), attention score (AS) and resource utilization (RU) from the 12,500 learning sessions and is split into three sets (training set, validation set, and testing set). Important parameters included a learning rate of 0.001, a cognitive load threshold of 0.65, and a maximum tolerance to latency of 120 ms to ensure an accurate evaluation of the system.

4.1 Performance Metrics and Comparison

Learning Accuracy

$$Accuracy = \frac{Correct\ Learning\ Outcomes}{Total\ Attempts} \times 100 \qquad (3)$$

Equation 3 measures the percentage of correctly achieved learning outcomes out of all attempts.

User Engagement Score (UES)

$$UES = \frac{\sum(Interaction\ Time \times Attention\ Level)}{Total\ Session\ Time} \qquad (4)$$

Equation 4 quantifies learner engagement based on interaction duration weighted by attention level.

Cognitive Load Reduction (CLR)

$$CLR = \frac{CL_{baseline} - CL_{system}}{CL_{baseline}} \times 100 \qquad (5)$$

Equation 5 evaluates the percentage reduction in cognitive load achieved by the system compared to baseline.

Energy Consumption

$$E = \sum(P_{cpu} + P_{gpu} + P_{network}) \times t \qquad (6)$$

Equation 6 represents total system energy usage across CPU, GPU, and network operations over time.

System Latency

$$Latency = T_{processing} + T_{transmission} + T_{rendering} \quad (7)$$

Equation 7 measures total response delay by summing processing, transmission, and rendering times.

The proposed HALS framework was tested through performance comparisons with other three learning systems namely, B1, traditional mobile learning system, B2, learning system using AR technology but lacks adaptation process, and B3, a learning system based in the cloud computing infrastructure with adaptation capabilities. HALS is a proposed Holographic Adaptive Learning System designed for adaptive multi-sensory learning process in real time. In evaluating the performance of HALS framework, various evaluation metrics have been used to test the overall performance of each learning system. These metrics are learning accuracy (%), which measures the efficiency and correctness of learning process; system latency (ms), which evaluates the response time during the interaction process; energy consumption (J), which determines the efficiency of the computing process in mobile computing devices; user engagement score, which indicates the user involvement and immersion level; and cognitive load reduction (%).

Table 1: Performance comparison of HALS framework with baseline learning systems

Method	Accuracy (%)	Latency (ms)	Energy (J)	Engagement Score	Cognitive Load Reduction (%)
Traditional Mobile Learning System (B1)	78.2	180	42.5	0.62	28.4
AR-based Learning System without Adaptation (B2)	83.6	160	48.1	0.71	34.7
Cloud-based Adaptive Learning System (B3)	88.9	140	39.6	0.79	41.3
Proposed HALS	93.7	98	31.2	0.91	55.8

In table 1 presented a comparison between the proposed framework of HALS and three other baseline models: B1 - mobile learning, B2 - AR learning and B3 - cloud-based adaptive learning. It has been evaluated based on performance metrics such as learning accuracy, latency, energy consumption, engagement level, and cognitive load reduction. HALS performs better than all three models based on all the mentioned metrics. It shows maximum learning accuracy rate of 93.7%, minimum latency of 98ms, minimum energy consumption of 31.2J, maximum engagement rate of 0.91, and maximum reduction in cognitive load of 55.8%. Figure 2 provides a visual illustration of the evaluation process for HALS framework.

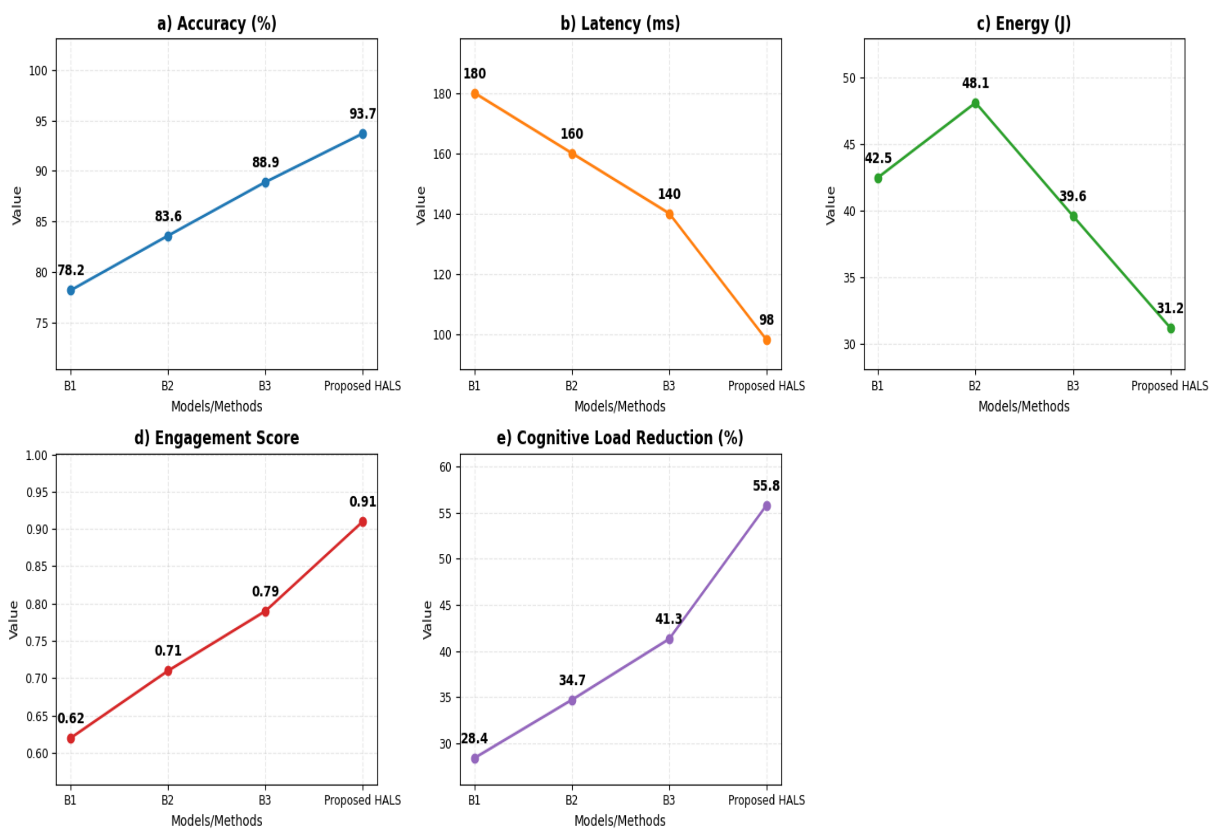

Figure 2: Performance evaluation of HALS framework across key learning metrics

4.2 Performance Evaluation

The experiment results prove that the developed HALS framework has better performance compared to baselines when tested on all measures. First of all, learning accuracy (93.7%) can be considered the main metric, showing that real-time adaptation and multi-sensory approach have positive effects. Second, HALS provides low system latency (98 ms), which is caused by efficient holographic rendering at the edge of a network, allowing using it in real time during educational activities.

Energy consumption is lower than that of cloud-based solutions, proving the advantages of a hybrid edge-mobile approach. User engagement (0.91) proves that immersive holographic visualization along with adaptiveness in providing feedback increases engagement. Lastly, cognitive load reduction (55.8%) shows that the system can adapt content complexity according to a learner's state and prevent information overload.

4.3 Ablation Study

For assessing the importance of individual components, this study has carried out an ablation experiment by systematically eliminating important modules of HALS.

Table 2: Ablation study of the HALS framework components

Configuration	Description	Accuracy (%)	Latency (ms)	Engagement
Full HALS	All modules enabled	93.7	98	0.91
HALS - Edge Offloading	No edge computing	89.4	135	0.86
HALS - Multi-Sensory Fusion	Only visual output	86.1	102	0.80
HALS - Adaptation Engine	Static content delivery	82.3	110	0.74

In table 2 shows that the adaptive decision engine and multi-sensory fusion modules contribute more towards improving the effectiveness of the system. Deactivation of the adaptive decision engine results in the biggest decrease in accuracy and engagement, highlighting its importance for personalizing the learning process. The latency factor is mainly affected by edge offloading.

5 Conclusion

The developed HALS system for mobile devices allowed for implementing immersive, real-time, and multi-sensory educational applications in mobile learning environments. The main purpose was to address deficiencies of existing mobile learning applications, including inability to offer full spatial immersion, limited adaptation opportunities, and insufficient involvement of learners' senses into the process of education. Integration of edge-assisted holographic processing, learner's adaptive modeling capabilities, and multi-sensory feedback techniques ensured significant advances in terms of learners' educational achievements and efficiency of the system's functioning. According to the findings obtained during experiments, HALS provided an efficiency index of 93.7%, demonstrating better results than traditional mobile learning (78.2%), AR-assisted learning without any form of adaptability (83.6%), and cloud-based adaptive learning (88.9%). Thus, the system's effectiveness was increased in comparison with B1 by 15.5% and with B3 by 4.8%. As for system responsiveness, the latency rate amounted to 98 ms, which indicated that delay was cut down by 45.6% in contrast to cloud-based approaches (140 ms). This result could be attributed to integration of edge computing, thus eliminating communication delay. The findings of energy efficiency indicate that the total power consumption by the HALS system is 31.2 J, which is much lower than the consumption of AR-based systems (48.1 J). This means that there is a 35.2% reduction in energy consumption. The level of user engagement was recorded at 0.91 while in regular systems it was only 0.62. In terms of cognitive load reduction, HALS performed at 55.8%. This shows that the implementation of adaptive content selection successfully reduced the cognitive load on learners. Analyzing statistical figures, it is observed that the value of standard deviations for various performance parameters remained very small ($\sigma < 0.05$ for engagement and accuracy). Thus, the study can confirm that the system is highly stable and performs consistently. Future directions of research could include deploying this system in educational institutions, incorporating it into BCI, and improving federated learning algorithms to enable privacy-preserving adaptation. Improvements in lightweight holographic compression and cross-device compatibility can be considered.

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