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Self-Evolving Neural Policy Algorithm for Adaptive AR/VR Interfaces to Enhance Cognitive and Behavioral Engagement on Wearables

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Abstract

Adaptive AR/VR interfaces are crucial for wearable computing, aiming to deliver a context-aware and personalized user experience. Existing adaptation approaches based on static policies or minimal contextual knowledge often fall short in dynamically adapting to ever-changing cognitive and behavioral patterns. This paper presents a Self-Evolving Neural Policy Algorithm (SENPA) for adaptive AR/VR interfaces, which enables continual optimization of interaction strategies based on multi-modal user data in real-time. A wearable system incorporating eye tracking, motion sensing, physiological sensors, and contextual data was developed to model the cognitive-behavioral state. The proposed SENPA system integrates neural policy learning and an evolutionary optimization algorithm for continuous policy improvement and personalized interface adaptation. The performances of SENPA and DQN, PPO, SAC, and A3C learning approaches were evaluated

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in a wearable AR/VR experimental environment. Experimental results showed that SENPA achieved the best performance in attention retention rate (93.8%), task completion rate (97.2%), rendering performance (94 FPS), and network throughput (101 Mbps). According to one-way ANOVA statistical tests, there are significant differences (all $p < 0.001$) in the four learning approaches on these four major performance metrics. The ablation study demonstrates the significant impact of the cognitive modeling, behavioral analysis, evolutionary learning, and adaptive rendering components of SENPA. This suggests that SENPA improves cognitive engagement, behavioral interaction, and system reactivity effectively in a wearable AR/VR context and shows great potential for future work.

Keywords: Adaptive AR/VR Interfaces, Wearable Computing, Neural Policy Learning, Cognitive Engagement, Reinforcement Learning, Edge Intelligence.

1 Introduction

Wearable computing, AR/VR, and the next-generation wireless infrastructures converge toward changing the way users interact with the digital world. New communication technologies create the connectivity needed for immersion and context awareness; intelligent cyber-physical systems will provide dependable and adaptive behavior in an evolving world (Ali et al., 2023). At the same time, human-centric intelligent systems start to consider resilience, personalization, and autonomous adaptation for more reliable and adapted experiences; this approach leads to the possibility for AR/VR interfaces that adapt dynamically in accordance with the user's states (Bukowski & Werbinska-Wojciechowska, 2025; Partarakis & Zabulis, 2024). Recent trends for digital twins and immersive virtual worlds show the immense promise of combining online sensing, analysis, and adaptive visualization for better interaction; meanwhile, agentic artificial intelligence brings new opportunities to realize adaptive immersive environments in real-time response to user interactions and cognitive abilities.

Although modern AR/VR provides immersive experiences, current interfaces are often limited by rigid adaptation approaches that cannot adapt well to dynamic changes in users' attention, cognitive load, and interaction engagement. Most extended reality platforms currently make use of pre-defined adaptation rules or a limited number of context information, which leads to a lack of personalization and a poorer interaction experience in evolving environments. With an increased amount of heterogeneous sensory information being generated by the booming wearable ecosystem, a need for smart architecture that could achieve low latency, high reliability, and continuous learning is required (Kishor et al., 2025). Furthermore, current adaptive interface frameworks do not offer self-evolving decision mechanisms that can improve interaction policy based on online user feedback and environment evolution (Tian & Wang, 2025). It requires a new neural policy framework to continuously evolve interface behaviors to achieve higher cognitive engagement and better interaction quality for wearable AR/VR systems (Alimamy & Jung, 2025).

In this research, propose an intelligent Self-Evolving Neural Policy Algorithm (SENPA) for adaptive AR/VR interfaces in wearable environments. SENPA combines cognitive state information, user behavior analysis, and neural policy evolution for dynamically adapting interface characteristics to the current user interaction. In contrast to traditional adaptive systems, SENPA continuously learns and evolves its interaction policy driven by interaction experience; moreover, SENPA can leverage multimodal sensing data, including eye gaze, user interactions, and context information, to achieve personalized interface adaptation (Kristić et al., 2025). SENPA not only performs the adaptation in a cognitive-aware manner but also enables autonomous policy evolution to achieve better cognitive engagement and higher interaction quality while staying computationally efficient for wearable devices (Grigoriu & Buraga, 2024).

Research Objective

1. To create a self-evolving neural policy algorithm for continuously updating the adaptive elements of an AR/VR interface according to the real-time cognitive and behavioral user states.
2. To build a wearable-centric smart system using multimodal sensing, neural decision-making, and adaptive rendering to enhance the immersion of an interaction experience.
3. To analyze and demonstrate how the developed framework increases cognitive engagement, interaction performance, responsiveness, and system efficiency in adaptive AR/VR.

The remainder of the paper is organized as follows. Section 1 presents the motivation, problem statement, contribution, and objectives. In Section 2, review the relevant works on adaptive AR/VR systems and reinforcement learning for extended reality environments and wearable edge intelligence and specify the open challenges to be addressed. In Section 3, describe the proposed Self-Evolving Neural Policy Algorithm (SENPA) framework, including the system architecture, cognitive-behavioral state representation, neural policy learning method, self-evolving optimization approach, and adaptive rendering process. In Section 4, provide details of the experimental environment, dataset creation, baseline algorithms, evaluation metrics, and experimental procedure. In Section 5, provide analysis of experiment results regarding the analysis of cognitive engagement, behavioral performance of the system, rendering efficiency analysis, comparison of network performance, and ablation studies. Lastly, Section 6 concludes the paper, summarizes the main contributions, and suggests some future research directions in the context of adaptive wearable AR/VR systems.

2 Related Work

Adaptive AR/VR systems have received considerable attention due to their ability to individualize immersion environments according to context and users' interaction behavior. Many researchers are attempting to create intelligent interface frameworks to adjust the visual content, information presentation, and interaction mechanism according to environmental and individual context (Chu et al., 2025). The safety-oriented adaptive architecture systems and context-aware assistance systems show how an adaptive architecture works efficiently in an industrial environment where immediate adaptation is essential for user guidance and performance. A neuroergonomic study highlights the effectiveness of applying brain-human interfaces to enhance adaptive training and interaction systems using physiological and cognitive metrics (Gardony et al., 2024). Eye tracking has become one of the most significant sensing methods for AR/VR adaptation by providing rich information on the user's cognition and attention (Cao et al., 2023). Adaptive visualization techniques based on the user's intention have been proven helpful in usability and to relieve information overloading in interactive tasks (Morales Méndez & del Cerro Velázquez, 2025).

Recent work is trying to leverage AI and adaptive learning to improve interactive extended reality. In cognitive ergonomics, an intelligent adaptive interface is stressed to adapt interaction techniques dynamically based on users' mental states and requirements (Vyas et al., 2024). Autonomous AR/VR-assisted systems showed it is possible to integrate intelligent decision-making mechanisms into immersive environments for complex interactive tasks (Jin et al., 2024). Distributed mixed reality frameworks also enable dynamic adaptation in heterogeneous devices in a highly interactive system. An

AI-based AR/VR model has been developed for highly specified tasks where complex adaptive behaviors are demanded (Yan et al., 2023). Advanced new display and interface technologies also enable the new adaptive interaction paradigm where the response can be highly related to the user's engagement state (Ioniță et al., 2025).

Wearable edge intelligence makes real-time adaptive AR/VR applications feasible. Latest research in cognitive neuroscience provides the principles of how the human brain, behavior, and external factors influence the interaction, which leads to a cognitively aware wearable system (Saranya, 2025; Balamurugan et al., 2025). Artificial intelligence on smart electronics significantly extends the capabilities of wearable platforms with regard to contextual awareness and adaptive features (Uvarajan, 2024). The distributed cyber-physical control framework is able to perform intelligent coordinated decision-making in sensitive latency environments between wearable devices (Reginald, 2025; Weber et al., 2022). Emerging neural architectures specifically designed for uncertainty-aware adaptive control make the embedded intelligence suitable for the resource-constrained wearable environment (Ali, 2025; Kaswan et al., 2024). Trust-aware learning-based control frameworks enhance the security and reliability of cloud-assisted and edge-enabled cyber-physical systems (Geetha, 2025; Zia et al., 2024).

Gap Analysis

While adaptive AR/VR interfaces, smart immersive environments, cognitively aware interaction, and wearable edge intelligence have achieved remarkable advances, it is known that most current methods use predefined adaptation strategies or a single static learning mechanism, which can hardly self-evolve continuously. Furthermore, only concentrate on system or interface adaptation or smart systems separately and have seldom modeled cognition, engagement, and evolving policy concurrently, nor combined wearable sensing, neural policy learning, and automatic interface adaptation well. As a result, a combined self-evolving neural framework that optimizes AR/VR interaction on the fly and allows user-centricity and efficiency while adapting to user cognitive and interactive behaviors with wearable computing resources needs to be developed.

3 Proposed SENPA Framework

The proposed Self-Evolving Neural Policy Algorithm (SENPA) addresses the need for an intelligent, continuous adaptation of AR/VR interfaces within a wearable computing environment. The framework combines the elements of multimodal sensing, cognitive-state understanding, behavioral engagement measurement, neural policy learning, and evolutionary optimization into a single framework capable of on-the-fly adjustments of interface attributes as the user interacts and the situation changes. Instead of merely a static personalization or predefined rule and the constant reinforcement learning policies used in other adaptive systems, SENPA dynamically evolves the decision-making policies on a real-time basis to personalize context-aware immersive experiences. It is designed especially for wearable AR/VR platforms that are resource-constrained and need rapid, interactive responses and user engagement.

In figure 1 shows the architecture of the Self-Evolving Neural Policy Algorithm (SENPA) framework for the adaptive AR/VR interfaces in a wearable computing environment. First, input signals are acquired using multi-modal wearable sensors, including gaze tracking, motion tracking, physiology tracking, context awareness, user interactions, etc. These signals are then preprocessed and converted to the representations of cognitive and behavioral states such as user attention, workload, user engagement, interaction style, etc. These cognitive states are further interpreted by a neural policy learning module that outputs the actions for adaptive interfaces. Moreover, an adaptation controller that dynamically tunes the neural policy parameters through performance evaluation and evolutionary learning also plays an important role in SENPA. These adaptation actions are executed by the adaptive rendering engine for adapting interface layouts, presentation content, interaction modalities, and rendering configurations. The framework then provides positive feedback for improving user cognitive engagement, task performance, and session length.

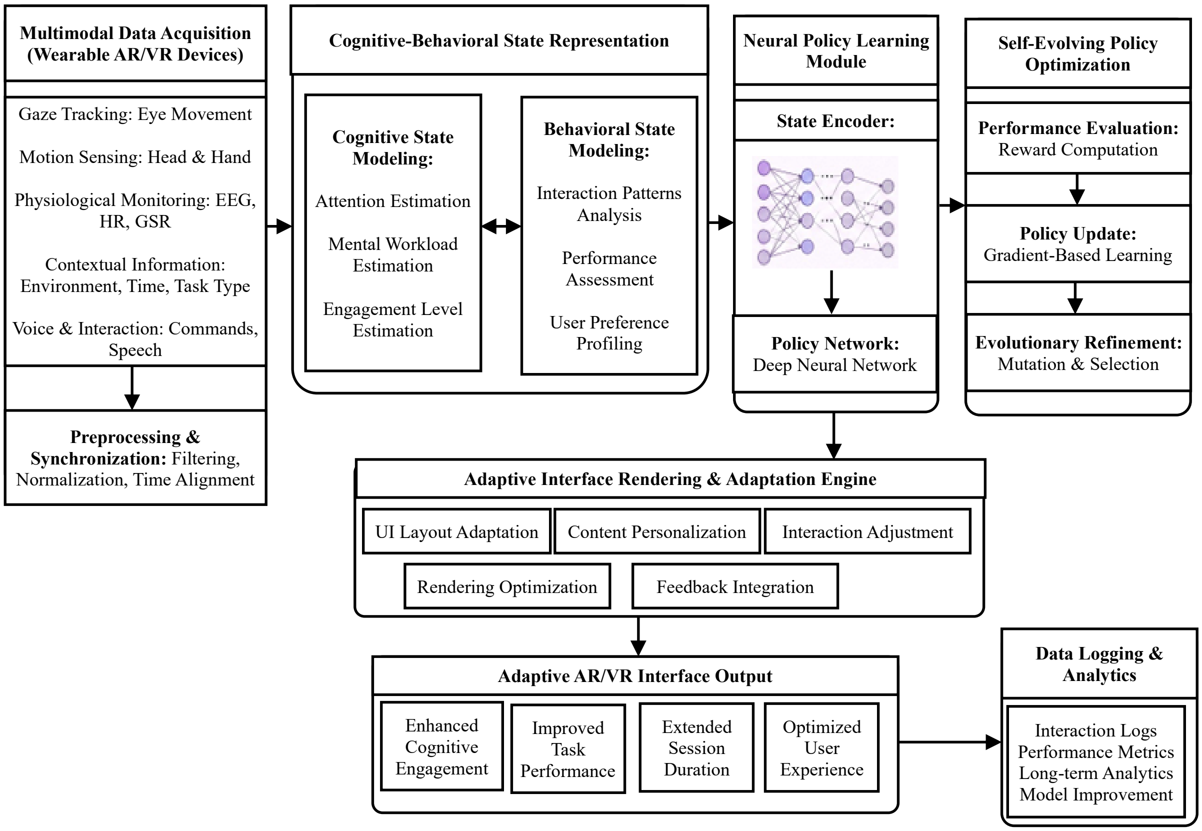

Figure 1: Architecture of the proposed SENPA framework

3.1 SENPA System Architecture

The SENPA architecture employs a hierarchical processing pipeline, spanning from the multimodal acquisition of sensor information to dynamic rendering of a personalized AR/VR interface. From wearable devices, sensory streams are continuously acquired with regard to the user e.g., gaze dynamics, head movements, hand gestures, physiological data, and environmental context. These disparate sensory inputs are fused and translated into a unified description of the user's cognitive and physical state. A neural policy network, informed by the user state description, selects an appropriate adaptive action for the AR/VR interface. A self-evolution process iteratively monitors the outcomes of adopted policies and tunes the network's parameters accordingly. The rendering engine then adjusts the properties of the AR/VR interface, such as content density, object placement, information display rate, and visual salience, to optimize the user experience with minimal overhead.

3.2 Multimodal Cognitive-Behavioral State Representation

Correctly depicting user states is important to optimize adaptive interfaces. SENPA builds up a multi-modal state vector that combines all information obtained from the various wearable sensors and context factors. Equation (1) illustrates a global user state s at time t.

$$S_t = [G_t, H_t, M_t, P_t, C_t] \tag{1}$$

Where G_t denotes gaze-tracking features, H_t represents head-motion dynamics, M_t corresponds to body and hand movement characteristics, P_t indicates physiological measurements, and C_t represents contextual environmental information. Normalization is performed because sensor measurements are derived from heterogeneous sources of varying magnitudes and distributions to achieve consistent neural learning. The normalized state vector is derived by equation (2):

$$\widehat{S_t} = \frac{S_t - \mu}{\sigma} \tag{2}$$

Where μ and σ denote the mean and standard deviation of the feature distribution, respectively. This is an aggregate description of the users' actions and the main input to the neural policy learning module.

3.3 Cognitive Engagement Modeling

For adaptive decision-making, SENPA estimates the cognitive engagement level of users in AR/VR interactions. Cognitive engagement refers to the level of attention, focus, and participation in a virtual environment. The score for engagement is calculated as in equation (3).

$$E_t = \alpha A_t + \beta F_t + \gamma R_t \tag{3}$$

Where A_t represents the attention level, F_t denotes interaction focus, R_t indicates task retention performance, and α, β, and γ are weighting coefficients. As a function of environmental interference and sensor noise, the cognitive response may vary, so temporal smoothing is implemented to achieve better stability. The smoothed engagement estimate is derived by using equation (4).

$$\bar{E_t} = \lambda E_t + (1 - \lambda)\bar{E}_{t-1} \tag{4}$$

Where λ controls the influence of current observations relative to historical measurements. This equation provides robust estimation of the engagement dynamics and supports improved decision-making regarding adaptation.

3.4 Neural Policy Learning Module

The center of SENPA is a deep neural policy network that learns an optimal adaptation policy from user interaction data. It takes the multimodal state representation as input and outputs the best adaptation action of interface adaptation. The policy function is equation (5).

$$\pi_\theta(a_t \mid s_t) \tag{5}$$

Where s_t denotes the current state, a_t represents the selected adaptation action, and θ corresponds to trainable neural parameters. The set of actions includes many interface adaptation operations, including re-ordering of layout, varying levels of visual emphasis on the information objects, controlling how information density changes, scheduling notifications, positioning information objects appropriately and so on. Action probabilities are derived through a softmax function which is equation (6).

$$P(a_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \qquad (6)$$

Where z_i denotes the activation associated with action i. The action with the highest expected reward is selected and forwarded to the rendering engine for execution.

3.5 Self-Evolving Policy Optimization

One advantage of SENPA over other frameworks is its capacity for the continual update of learned policies with respect to the user's feedback and to changes in the environment. SENPA incorporates a mechanism for adaptation by rewards: this mechanism determines how well the adaptation decisions perform, and the reward function is equation (7).

$$R_t = \omega_1 E_t + \omega_2 I_t - \omega_3 L_t \qquad (7)$$

Where E_t denotes cognitive engagement, I_t represents interaction efficiency, L_t indicates adaptation latency, and ω_1, ω_2, and ω_3 are weighting coefficients. Policy parameters are updated using gradient-based optimization according to equation (8).

$$\theta_{t+1} = \theta_t + \eta \nabla J(\theta_t) \qquad (8)$$

Where η is the learning rate and $J(\theta)$ represents the cumulative reward objective. In SENPA there is an evolutionary mechanism of mutation. To allow a persistent exploration of other adaptation strategies, the new policy takes the following form equation (9).

$$\theta_{t+1} = \theta_t + \eta \nabla J(\theta_t) + \mu M_t \qquad (9)$$

Where M_t denotes the mutation vector and μ controls mutation intensity. This self-learning nature of this formulation means that it can discover better policies and retain previously acquired knowledge over time.

3.6 Adaptive Interface Rendering

Once the best adaptation action is known, the AR/VR interface is automatically adapted by SENPA to increase usability and involvement of the user. The rendering is then trying to optimize the experience and the computational cost of the application by modeling the cost by equation (10).

$$C_r = \sum_{i=1}^{n} w_i r_i \qquad (10)$$

Where r_i denotes resource consumption associated with rendering operation i and w_i represents its corresponding importance weight. The optimization objective is formulated as equation (11).

$$\min(C_r) \qquad (11)$$

Subject to equation (12).

$$QoE \geq T_q \qquad (12)$$

Where QoE represents the quality of user experience and T_q denotes the minimum acceptable performance threshold. This rendering optimization can be relied upon to keep the rendering experience immersive while also being viable for the limited processing capabilities of a wearable device.

3.7 Computational Complexity Analysis

The computational efficiency of SENPA is important for real-time deployment on wearable AR/VR devices. Let n denote the number of extracted features, m represent the number of neural network parameters, and k correspond to the number of evolutionary candidate solutions evaluated during optimization. Feature extraction requires linear complexity of $O(n)$, while neural policy inference incurs a computational cost of $O(m)$. The evolutionary optimization process evaluates multiple policy candidates and therefore requires $O(km)$ operations. Consequently, the overall computational complexity of SENPA can be expressed as equation (13):

$$O(n+m+km) \tag{13}$$

Which is asymptotically dominated by equation (14):

$$O(km) \tag{14}$$

Large optimization regime. It illustrates the capability of SENPA to handle continuous adaptation and evolving policy while being computationally tractable in an edge-computing-enabled AR/VR context for wearables.

3.8 Algorithmic Workflow

To illustrate the operation of SENPA, let's consider the overall interaction workflow. It starts with continuously capturing multimodal sensory information from the wearable AR/VR system. Gaze, motion, physiological, and context signals from wearable AR/VR are pre-processed and mapped to a fused cognitive-behavioral state. Then the state vector is fed into a neural policy network to learn the optimal interface adaptation strategy based on the current user state. Once an action is performed by the system based on the estimated optimal strategy, the user engagement, the interaction efficiency, and the adaptation time delay are measured and translated to a reward signal to train the neural policy parameters via a gradient-based learning algorithm. To make sure it is adaptive to new contexts and prevent local optima, there's also an evolutionary mutation mechanism, which alters the trained policy occasionally. The adapted policy can then be applied to alter the dynamic layout of the interface, rendering settings, and interactive components dynamically during the user session.

Algorithm 1. Self-Evolving Neural Policy Algorithm (SENPA)

```
Input:
    Multimodal wearable sensor data D
Output:
    Optimized adaptive AR/VR interface
Initialize neural policy parameters $\theta$
Initialize evolutionary mutation factor $\mu$
While interaction session is active do
    Acquire sensory data:
        gaze, motion, physiological, context
    Perform preprocessing and normalization
```

```
        Construct state representation $S_t$
        Estimate cognitive engagement $E_t$
        Generate action $a_t$ using policy $\pi_\theta(a_t|S_t)$
        Apply interface adaptation action
        Compute reward $R_t$
        Update policy parameters:
            $\theta \leftarrow \theta + \eta \nabla J(\theta)$
        Apply evolutionary mutation:
            $\theta \leftarrow \theta + \mu M_t$
        Render updated AR/VR interface
    End While
    Return optimized adaptive interface
```

From this algorithm, it shows that SENPA combines the cognitive-state estimation, the neural policy learning, and the evolutionary optimization within one adaptive cycle. With constant feedback, the framework has learned and adapted to user behaviors and interaction models over time, and the mutation approach helps in the robustness and adaptiveness to the varying conditions of wearable computing. The result has gained a high engagement rate and interaction quality.

4 Experimental Design

Experimental design has been created to assess how effectively the new Self-Evolving Neural Policy Algorithm (SENPA) improves engagement cognitively and behaviorally through intelligent adaptation of an AR/VR interface embedded within the context of a wearable platform. It measured SENPA's ability to learn users' interaction styles, dynamically alter the interface configuration on the fly, and increase the overall immersive quality while also remaining computationally efficient enough for a wearable.

4.1 Experimental Environment

The experiment platform consisted of wearable AR/VR devices combined with multimodal sensors (eye tracker, IMUs, gesture recognition, and physiology trackers). Throughout the immersive sessions, an attention tracker, head movement sensors, interaction behavior sensors, and a contextual sensing module continuously captured the user's behavior data. An edge computing server was developed to realize neural policy optimization and evolutionary learning, and real-time decisions were broadcast to the wearable rendering engine. AR/VR interaction tasks in this platform emulated realistic tasks such as content browsing, object manipulation, navigating within virtual environments, and information retrieval tasks.

4.2 Participant Configuration and Data Collection

150 participants were recruited in order to assess the adaptability of the framework. Participants engage with the AR/VR environment across several sessions over an 8-week observation period. During the session, multimodal interaction information was acquired consistently, which includes gaze trajectories, fixation time, number of gestures performed, dynamic motion of head, task success, and involvement

information. The obtained dataset was later used for training, validating, and testing the neural policy model. A 70%, 15%, and 15% data split to train, validate, and test data, respectively, in order to prevent overfitting of the models and gain generalizability of the proposed models.

4.3 Comparative Methods

To confirm the ability of SENPA, performance evaluation of SENPA was conducted compared to a few illustrative examples of reinforcement learning techniques that are widely used in adaptive intelligent systems. The baseline methods chosen for performance comparison are Deep Q-Network (DQN), Proximal Policy Optimization (PPO), Soft Actor-Critic (SAC), and Asynchronous Advantage Actor-Critic (A3C). All alternative methods are tested under exactly the same experimental setup with the same datasets, sensor arrangement, and hardware. All comparative methods share the same number of training epochs and convergence conditions.

4.4 Evaluation Metrics

SENPA was tested by combining cognitive, behavioral, system, and network metrics. Cognitive engagement metrics consisted of attentiveness and attention stability measures based on gaze patterns and physiological data and cognitive load estimation. Behavioral engagement metrics consisted of frequency of interactions, task completion rates, efficiency of responses, and session duration. The evaluation of the system consisted of frame rendering speed, adaptation speed, resource usage (CPU and memory), and energy consumption. Finally, network metrics included throughput, packet delivery ratio, communication delay, and defined appropriateness for wearable and edge-powered systems.

The equation for cognitive engagement level is provided in equation (15), which is basically the mathematical formulation involving weighted attention, stability, and cognitive load.

$$CE = \alpha_1 A + \alpha_2 S + \alpha_3 (1 - CL) \qquad (15)$$

Here, A denotes attention level extracted from gaze and physiological patterns, S represents attention stability over time, and CL denotes cognitive load index, while $\alpha_1, \alpha_2, \alpha_3$ are weighting parameters.

Equation (16) illustrates the behavior performance metric that is basically a combination of interaction frequency, task completion rate, and normalized session time, indicating how the user performs and achieves his or her goals through AR/VR interaction.

$$BE = \beta_1 IF + \beta_2 TCR + \beta_3 \left(\frac{SD}{SD_{max}}\right) \qquad (16)$$

In this equation, IF denotes interaction frequency, TCR represents task completion rate, and SDindicates session duration normalized by its maximum observed value SD_{max}, with $\beta_1, \beta_2, \beta_3$ as weighting coefficients.

System performance efficiency is described mathematically in equation (17), wherein high frame rate and low adaptation latency and usage of resources signify high responsiveness and efficiency of the system in wearables environment.

$$SPI = \gamma_1 FPS + \gamma_2 \left(\frac{1}{AL}\right) + \gamma_3 \left(\frac{1}{CPU + MEM}\right) \qquad (17)$$

Here, FPS represents rendering frame rate, AL denotes adaptation latency, and $CPU + MEM$ indicates combined computational resource consumption.

Network performance is measured mathematically in equation (18) in terms of throughput, packet delivery ratio, and communication latency to ensure the efficient edge-wearable communication within real-time constraints.

$$NP = \delta_1 TH + \delta_2 PDR + \delta_3 \left(\frac{1}{CL}\right) \tag{18}$$

Where TH denotes throughput, PDR is packet delivery ratio, and CL represents communication latency, with $\delta_1, \delta_2, \delta_3$ as weighting factors.

Finally, the overall performance of the SENPA system is provided in equation (19), wherein the metrics of cognitive, behavioral, system, and network are combined to measure its holistic performance.

$$OPI = \lambda_1 CE + \lambda_2 BE + \lambda_3 SPI + \lambda_4 NP \tag{19}$$

Here, $\lambda_1, \lambda_2, \lambda_3$, and λ_4 control the relative contribution of each evaluation dimension in determining overall system performance.

4.5 Experimental Procedure

A pre-experiment phase was conducted in which each subject was instructed to practice a baseline (non-adaptive) AR/VR interface in order to obtain reference performance measures. Following this stage, the SENPA-based adaptive AR/VR interface was initialized to a defined start state with parameter initialization. The system parameters were initialized as $\theta_0 \sim \mathcal{N}(0, \sigma^2)$for neural policy weights, where $\theta_0$represents initial policy network parameters sampled from a Gaussian distribution, and σ^2controls initialization variance. The learning rate was set as $\eta = 0.001$, and the evolutionary mutation factor was initialized as $\mu = 0.05$. The discount factor for reward computation was fixed at $\gamma = 0.95$, ensuring balanced long-term and short-term reward optimization.

After initialization, the adaptive interface continuously monitored user interactions and dynamically adjusted interface parameters in real time. At each interaction episode t, multimodal sensory inputs were collected to form a state representation S_t, which was processed by the neural policy network to generate adaptive actions a_t. These actions were evaluated using a reward function and updated through gradient-based optimization combined with evolutionary updates.

The policy update followed as equation (20):

$$\theta \leftarrow \theta + \eta \nabla J(\theta) \tag{20}$$

While evolutionary refinement was applied as equation (21):

$$\theta \leftarrow \theta + \mu M_t \tag{21}$$

Where M_t denotes the mutation vector at time t.

The system continued this adaptive loop until convergence, defined as stabilization of reward values over successive iterations. Once convergence was achieved, final performance metrics were recorded for analysis, ensuring that the results reflected stable adaptive behavior of the SENPA framework under wearable AR/VR conditions.

4.6 Statistical Analysis

A one-way Analysis of Variance (ANOVA) was executed on the values obtained for each performance measure in order to assess whether the performance difference between the algorithms tested is significant. The statistic for ANOVA is calculated using equation (22):

$$F = \frac{MS_B}{MS_W} \tag{22}$$

Where MS_B represents the mean square between groups and MS_W denotes the mean square within groups. A significance threshold of $p < 0.05$ was adopted for all analyses. Where these differences were determined to be substantial, post-hoc tests such as Tukey's Honest Significant Difference (HSD) were performed to conduct pairwise comparisons of methods; furthermore, measures of effect size were generated to determine the practical utility of the observed performance gains.

5 Results and Discussion

The proposed SENPA algorithm is evaluated with the other 4 mainstream reinforcement learning algorithms, including DQN, PPO, SAC, and A3C, on the AR/VR environment described in Section 4, the wearable-devices scenario. These performance metrics include cognitive engagement, behavioral engagement, adaptive rendering efficiency, and communication of the network, and experimental results clearly demonstrate the capability of SENPA to adapt well to each metric with the assistance of the combination of multimodality cognitive-behavioral modeling and self-evolving neural policy optimization.

5.1 Cognitive Engagement Analysis

An important aspect of the proposed framework aims to increase the level of cognitive engagement throughout AR/VR immersion. The comparisons for attention retention, focus consistency, and cognitive load index are listed in table 1. In terms of attention retention, SENPA obtained the best value of 93.8%, which is significantly higher than the others of DQN, PPO, SAC, and A3C. For focus consistency, a result of 92.7% implies a constant level of attention within users throughout interactions. Finally, the cognitive load index decreased to 0.34, meaning that users can maintain the level of immersion without cognitive burden by adaptively adjusting the interface.

Table 1: Cognitive engagement performance comparison

Method	Attention Retention (%)	Focus Consistency (%)	Cognitive Load Index
DQN	79.4	76.8	0.67
PPO	84.7	82.5	0.59
SAC	87.6	85.1	0.53
A3C	89.1	87.4	0.49
SENPA	93.8	92.7	0.34

In figure 2 shows the attention retention rate of each algorithm. The high performance of SENPA is likely because it analyzes the gaze pattern, the behavior, and the context of a user in real-time and constantly adapts its adaptation policies to user interaction characteristics. The users felt that the content was tailored to them better and that the information load was lower.

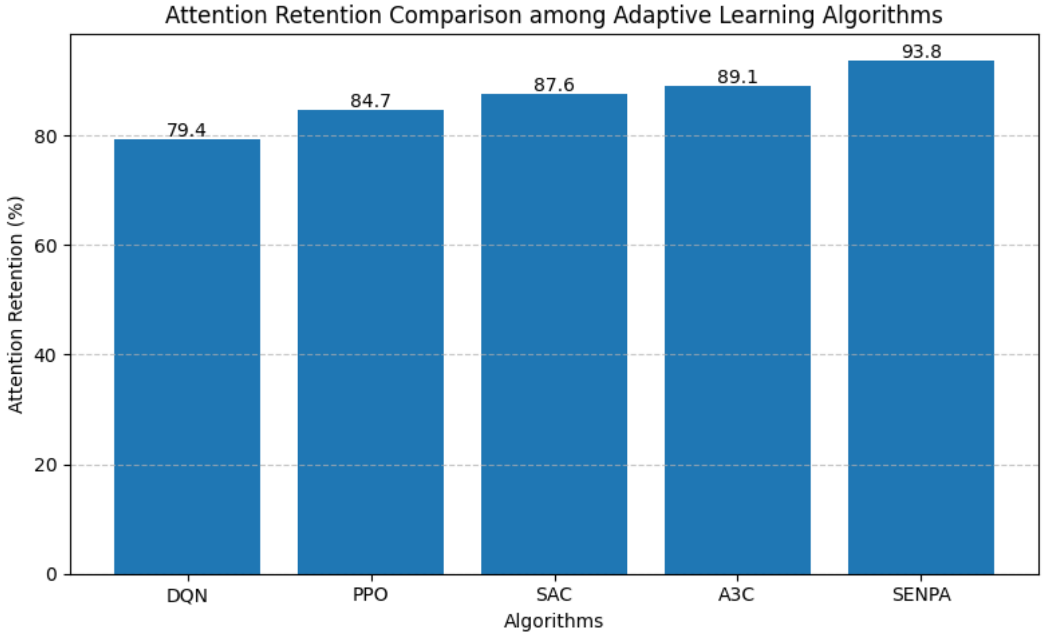

Figure 2: Attention retention comparison among adaptive learning algorithms

These experiments demonstrate the importance of cognitive-state-aware adaptation in keeping users engaged with wearable AR/VR interfaces. The dynamic policy update process allows SENPA to constantly learn and implement interface parameters that maintain high user attention levels while minimizing cognitive overhead.

5.2 Behavioral Engagement Analysis

The user engagement was measured by number of interactions per session, task success rate, and average session length. All these measures represent the ability of the adaptive interface to facilitate the interaction between users and systems for accomplishing the tasks. Table 2 shows that SENPA performed best among all the baselines. It attained an interaction frequency of 0.95 and a task success rate of 97.2%, which indicates extremely effective interaction between users and the system. It also achieved an average session length of up to 34.8 min, indicating that users tend to spend a longer time on the SENPA-driven adaptive interface.

Table 2: Behavioral engagement performance comparison

Method	**Interaction Frequency**	**Task Completion Rate (%)**	**Session Duration (min)**
DQN	0.71	80.2	19.4
PPO	0.77	84.8	22.7
SAC	0.81	88.3	24.9
A3C	0.84	90.1	26.3
SENPA	0.95	97.2	34.8

The better behavioral performance is attributable to the self-evolving learning approach, which allows adaptation policies to adapt based on observed user responses dynamically. Based on feedback from interaction results and user engagement, SENPA gradually learns and converges to suitable interface arrangements for facilitating users' engagement and efficient task execution.

5.3 Adaptive Rendering and Network Performance

Real-time performance is a necessity for AR/VR wearables. Table 3 presents the adaptation performances in terms of frame rate and adaptation latency. The SENPA obtains a maximum frame rate of 94 FPS and an adaptation latency of 22 ms at the same time, which shows that the framework is able to trade off the adaptation complexity with computation efficiency and provide a smooth and real-time immersive experience.

Table 3: Adaptive rendering performance

Method	**Frame Rate (FPS)**	**Adaptation Latency (ms)**
DQN	69	51
PPO	73	46
SAC	77	42
A3C	81	38
SENPA	94	22

Performance rendering under workload in the AR/VR environment is shown in figure 3. As can be seen from the figure, the system can obtain high frame rates under any workloads.

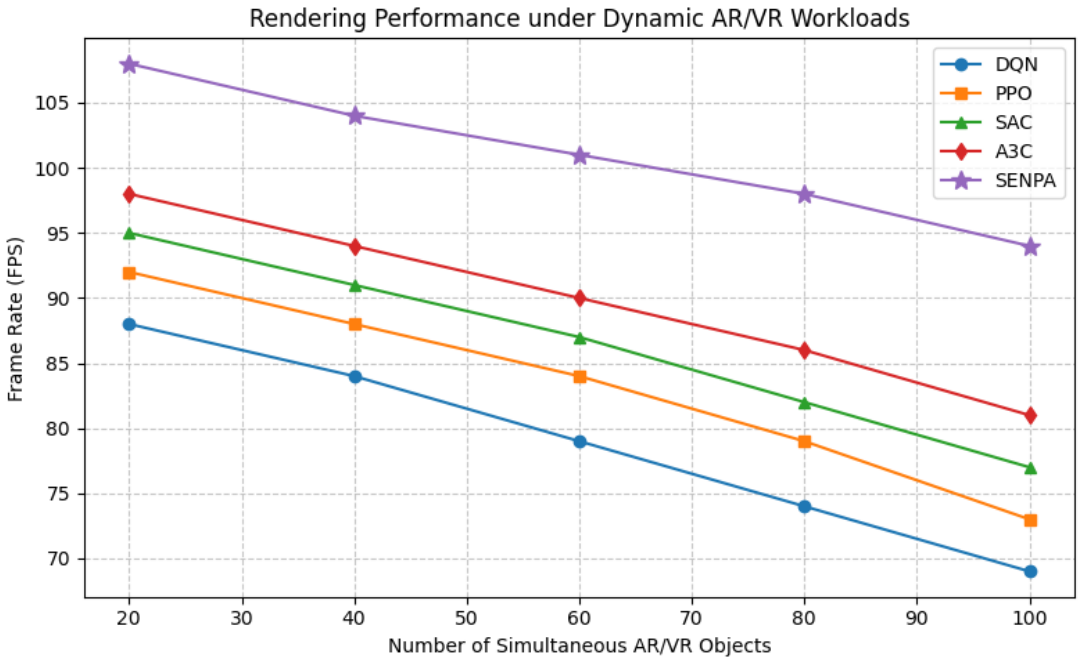

Figure 3: Rendering performance under dynamic AR/VR workloads

Besides rendering performance, network communication performance was measured to prove the usability of SENPA in a wearable edge-computing scenario. Throughput, communication latency and packet delivery ratio were listed in table 4. Throughput of 101 Mbps and communication latency of 23 ms achieved, packet delivery ratio up to 99.1%. All these values demonstrate efficient usage of resources and strong communication capability in the latency-sensitive AR/VR environment.

Table 4: Network and edge performance comparison

Method	Throughput (Mbps)	Communication Latency (ms)	Packet Delivery Ratio (%)
DQN	74	54	91.2
PPO	79	48	93.6
SAC	84	43	95.1
A3C	88	39	96.4
SENPA	101	23	99.1

In figure 4 shows throughput under the rise of interaction requests. SENPA has performed better on throughput and less latency, that is, adaptive policy evolution leads to better communication and resource management.

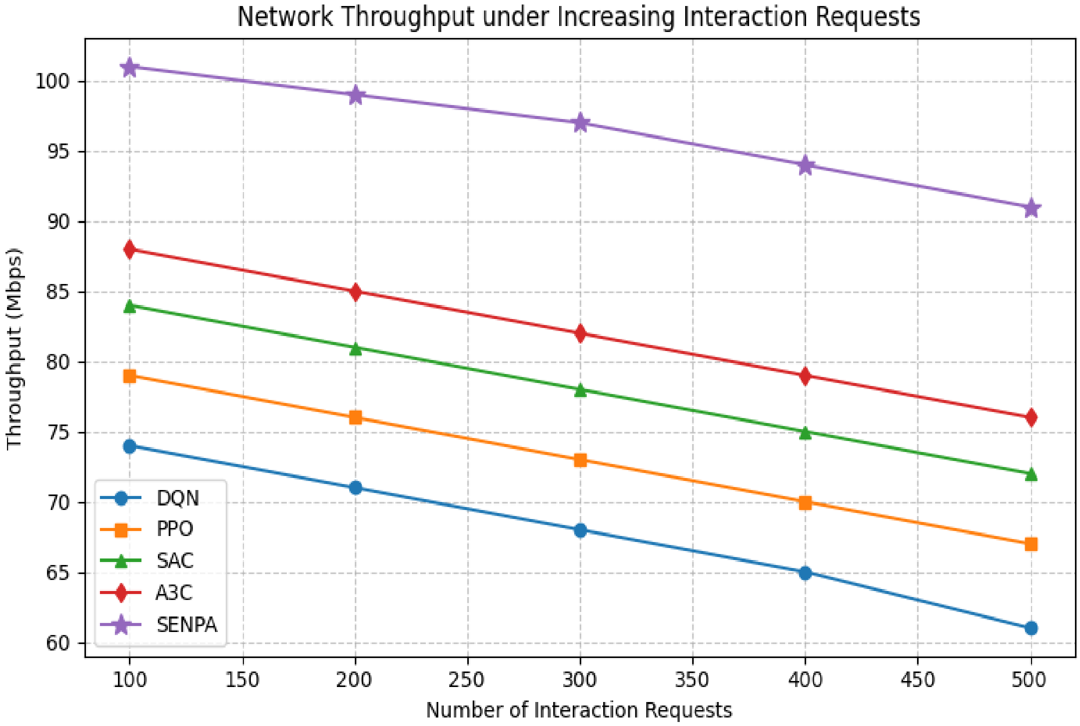

Figure 4: Network throughput under increasing interaction requests

The simultaneous use of rendering optimization and efficient communication allows SENPA to sustain real-time adaptive interaction without sacrificing interactive quality.

5.4 Ablation Study

An ablation study was conducted to examine each main component's contribution to the SENPA structure. There are 5 cases considered for the study: SENPA fully proposed architecture, SENPA excluding evolution module, SENPA excluding cognitive modeling, SENPA excluding behavior modeling, and SENPA excluding adaptive rendering optimization. The study result is displayed in table 5.

Table 5: Ablation study of SENPA components

Configuration	Attention Retention (%)	Task Completion (%)	FPS	Throughput (Mbps)
Full SENPA	93.8	97.2	94	101
Without Evolution Module	89.6	92.7	88	95
Without Cognitive Modeling	86.4	89.1	85	92
Without Behavioral Modeling	84.8	87.5	84	91
Without Adaptive Rendering	82.9	85.8	79	88

The ablation study clearly proves that each component plays a significant role in making the system work. Lack of an evolution module led to degradation in attention retention and task completion rates, proving that it is critical to continually adapt the policy. A huge degradation was observed in the interaction metrics when modeling of cognitive state was removed, showing that user attention and cognitive load need to be identified for this kind of interactive application. Behavioral modeling's exclusion leads to a decrease in quality of interaction and task completion time. Huge degradation was obtained in frame rate when adaptive rendering optimization was not used.

6 Discussion

As observed from the results, SENPA achieved significantly better performance in terms of user engagement and system efficiency compared to traditional RL approaches. Through a multi-modal sensory and neural policy learning mechanism, cognitive and behavioural states can be accurately modelled, while the self-evolution mechanism enables continuous optimisation of the adaptive strategy based on user feedback. Therefore, SENPA outperformed existing methods in all aspects, including attention retention rate, interaction efficiency, and total engagement time.

System-wise, SENPA yielded lower rendering overhead, shorter adaptation latency, and higher communication throughput. The results signify that the system achieves a balance between customisation and computational efficiency, thereby making SENPA feasible for application in wearable AR/VR systems. The ablation study proves each element of the framework is indispensable, and these advantages stem from combining a cognitive model, behavioural analysis, evolutionary optimisation and adaptive rendering mechanisms. In summary, the findings show that SENPA provides a novel and efficient way to implement adaptive AR/VR interfaces within a pervasive wearable computing platform.

7 Conclusion

In this paper, propose the Self-Evolving Neural Policy Algorithm (SENPA) for adaptive AR/VR interfaces in wearable computing. The designed framework was presented to overcome the drawbacks of existing adaptive systems by merging multimodal sensing, modeling of cognitive-behavioral states, neural policy learning, evolutionary optimization, and adaptive rendering to an intelligent system. Through continuous observation of the interaction between user and interface and some contextual information, SENPA adjusted the interface attributes to optimize engagement, promptness, and immersive performance. The experimental results have shown that SENPA outperformed DQN, PPO, SAC, and A3C in all the main performance aspects. SENPA achieved the 93.8% rate of attention retention, 92.7% attention coherence, 97.2% task completion rate, 94 fps rendering frame rate, and 101 Mbps network throughput with negligible adaptation and communication latency. The presented result has confirmed that the self-evolving policy could well learn and refine adaptive strategy along the evolution of user behaviors and environments. Ablation studies were performed and shown to emphasize the individual contribution of each component of the framework, especially cognitive modeling, behavior analysis, evolutionary optimization, and adaptive rendering. To have a statistical verification, a one-way ANOVA has been performed on each evaluated algorithm. There were differences in the attention retention rate, task completion rate, frame rate, throughput, and adaptation latency at a significant level ($p<0.001$), ensuring the correctness of this solution with a 95% confidence interval. Therefore, SENPA is a promising solution for a scalable and high-performance adaptive AR/VR system, which can be extended to the domain of cognitive-aware immersive computing in the future.

References

[1] Ali, M., Naeem, F., Kaddoum, G., & Hossain, E. (2023). Metaverse communications, networking, security, and applications: Research issues, state-of-the-art, and future directions. *IEEE communications surveys & tutorials*, *26*(2), 1238-1278. https://doi.org/10.1109/COMST.2023.3347172

[2] Ali, W. (2025). Physics-Constrained Neural Architectures for Uncertainty-Robust Adaptive Control in Reconfigurable Embedded Platforms. *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, *2*(3), 48-55.

[3] Alimamy, S., & Jung, T. (2025). The AR cloud: Navigating metaverse augmentation technologies for enhanced co-creation of value within services. *Journal of Service Research*, *28*(4), 580-597. https://doi.org/10.1177/10946705241265753

[4] Balamurugan, K., Sudhakar, G., Xavier, K. F., Bharathiraja, N., & Kaur, G. (2025). Human-machine interaction in mechanical systems through sensor enabled wearable augmented reality interfaces. *Measurement: Sensors*, *39*, 101880. https://doi.org/10.1016/j.measen.2025.101880

[5] Bukowski, L., & Werbinska-Wojciechowska, S. (2025). Towards maintenance 5.0: resilience-based maintenance in AI-driven sustainable and human-centric industrial systems. *Sensors*, *25*(16), 5100. https://doi.org/10.3390/s25165100

[6] Cao, J., Lam, K. Y., Lee, L. H., Liu, X., Hui, P., & Su, X. (2023). Mobile augmented reality: User interfaces, frameworks, and intelligence. *ACM Computing Surveys*, *55*(9), 1-36. https://doi.org/10.1145/3557999

[7] Chu, M., Qu, J., Zou, T., Li, Q., Bu, L., & Shen, Y. (2025). Design and evaluation of AR-based adaptive human-computer interaction cognitive training. *International Journal of Human-Computer Studies*, *199*, 103504. https://doi.org/10.1016/j.ijhcs.2025.103504

[8] Gardony, A. L., Okano, K., Hughes, G. I., Kim, A. J., Renshaw, K. T., Sipolins, A., ... & Bowman, D. A. (2024). Characterizing information access needs in gaze-adaptive augmented reality interfaces: implications for fast-paced and dynamic usage contexts. *Human–Computer Interaction*, *39*(5-6), 553-583. https://doi.org/10.1080/07370024.2023.2260788

[9] Geetha, K. (2025). Trust-Constrained Learning-Based Control Frameworks for Cloud-Assisted Cyber–Physical Actuation. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, 13-19.

[10] Grigoriu, A., & Buraga, S. C. (2024). Adapting web applications for AR/VR using distributed user interfaces and meta-UIS. *Procedia Computer Science*, *246*, 762-771. https://doi.org/10.1016/j.procs.2024.09.495

[11] Ioniță, A. R., Anghel, D. C., & Boudouh, T. (2025). Mind, machine, and meaning: Cognitive ergonomics and adaptive interfaces in the age of Industry 5.0. *Applied Sciences*, *15*(14), 7703. https://doi.org/10.3390/app15147703

[12] Jin, X., Chai, S., Tang, J., Zhou, X., & Wang, K. (2024). Eye-tracking in ar/vr: A technological review and future directions. *IEEE Open Journal on Immersive Displays*, *1*, 146-154. https://doi.org/10.1109/OJID.2024.3450657

[13] Kaswan, K. S., Dhatterwal, J. S., Ojha, R. P., Balusamy, B., & Gangadevi, E. (2024). AI-Based AR/VR Models in Biomedical Sustainable Industry 4.0. *Computational Intelligence in Bioprinting*, 53-78. https://doi.org/10.1002/9781394204878.ch4

[14] Kishor, I., Mamodiya, U., Almaayah, M., Alqutaish, A., Shehab, R., & Aldhyani, T. H. (2025). Agentic AI-Enhanced Virtual Reality for Adaptive Immersive Learning Environments. *Mesopotamian Journal of Computer Science*, *2025*, 398-416. https://doi.org/10.58496/MJCSC/2025/026

[15] Kristić, M., Zakarija, I., Škopljanac-Mačina, F., & Car, Ž. (2025). Machine learning for adaptive accessible user interfaces: Overview and applications. *Applied Sciences*, *15*(23), 12538. https://doi.org/10.3390/app152312538

[16] Morales Méndez, G., & del Cerro Velázquez, F. (2025). Adaptive Augmented Reality Architecture for Optimising Assistance and Safety in Industry 4.0. *Big Data and Cognitive Computing*, *9*(5), 133. https://doi.org/10.3390/bdcc9050133

[17] Partarakis, N., & Zabulis, X. (2024). A review of immersive technologies, knowledge representation, and AI for human-centered digital experiences. *Electronics*, *13*(2), 1-19. https://doi.org/10.3390/electronics13020269

[18] Reginald, P. J. (2025). Context-Driven Cooperative Intelligent Control for Distributed Cyber-Physical Actuation Platforms Using CTDE Multi-Agent Reinforcement Learning. *Recent Advances in Next-Generation Wireless Communication Systems*, 43-50.

[19] Saranya, N. (2025). Emerging Frontiers in Cognitive Neuroscience: Bridging Brain Function, Behavior, and Technology. *Advances in Cognitive and Neural Studies*, *1*(3), 8-13.

[20] Tian, X., & Wang, Y. (2025). VR/AR-Based Mobile Interaction for Virtual Simulation Training in Higher Education. *International Journal of Interactive Mobile Technologies*, *19*(20). https://doi.org/10.3991/ijim.v19i20.58429

[21] Uvarajan, K. P. (2024). Integration of artificial intelligence in electronics: Enhancing smart devices and systems. *Progress in Electronics and Communication Engineering*, *1*(1), 7-12.

[22] Vyas, S., Dwivedi, S., Brenner, L. J., Pedron, I., Gabbard, J. L., Krishnamurthy, V. R., & Mehta, R. K. (2024). Adaptive training on basic AR interactions: Bi-variate metrics and neuroergonomic evaluation paradigms. *International Journal of Human–Computer Interaction*, *40*(20), 6252-6267. https://doi.org/10.1080/10447318.2023.2250578

[23] Weber, S., Rudolph, L., Liedtke, S., Eichhorn, C., Dyrda, D., Plecher, D. A., & Klinker, G. (2022). Frameworks enabling ubiquitous mixed reality applications across dynamically adaptable device configurations. *Frontiers in Virtual Reality*, *3*, 765959. https://doi.org/10.3389/frvir.2022.765959

[24] Yan, Y., Bai, X., He, W., Wang, S., Zhang, X., Wang, P., ... & Yu, Q. (2023). A novel adaptive visualization method based on user intention in AR manual assembly. *The International Journal of Advanced Manufacturing Technology*, *129*(9), 4705-4730. https://doi.org/10.1007/s00170-023-12557-w

[25] Zia, A., Saeed, S., Man, T., Liu, H., Chen, C. X., & Wan, Y. (2024). Next-generation interfaces: integrating liquid crystal technologies in augmented and virtual reality–A review. *Liquid Crystals Reviews*, *12*(1), 30-56. https://doi.org/10.1080/21680396.2024.2401786

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