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ADAPTIVE LEARNING IN MIXED REALITY: NEW HORIZONS FOR PERSONALIZED EDUCATION

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Abstract. The integration of Artificial Intelligence (AI) and Mixed Reality (MR) in education is revolutionizing the way learners interact with digital content. This paper explores how AI-powered adaptive learning systems, combined with Unreal Engine 5 (UE5), can enhance immersive educational experiences. UE5 provides high-fidelity virtual environments, enabling interactive and engaging simulations that respond dynamically to learners' needs. AI algorithms analyze user interactions, preferences, and cognitive load to personalize content in real-time, fostering deeper engagement and improved knowledge retention. The study examines key applications, including gesture recognition, voice interaction, and real-time adaptation of virtual learning environments. Challenges such as optimization for real-time performance, ethical considerations, and user accessibility are also discussed. The findings highlight the potential of AI-driven MR experiences in reshaping education, making learning more accessible, interactive, and personalized.

Keywords: Mixed Reality; Artificial Intelligence; Unreal Engine 5; Adaptive Learning; Immersive Education; Virtual Environments

1. Introduction

In recent years, technological advancements—particularly in the fields of Artificial Intelligence (AI) and Mixed Reality (MR)—have significantly transformed the landscape of education. Traditional educational methods, which rely on static learning materials and linear information delivery, are increasingly being replaced by dynamic, adaptive, and immersive approaches. In this context, the concept of adaptive learning, supported by technologies such as MR and AI, has emerged as a key solution for personalizing the learning process, enhancing learner motivation, and optimizing educational outcomes (Feng et al., 2025).

Mixed Reality represents a synthesis between augmented reality (AR) and virtual reality (VR) (Lee et al., 2024), enabling real-time interaction with both digital and physical objects. MR environments offer unique opportunities for creating interactive and highly detailed educational simulations that can be tailored to the individual needs of each learner. These environments not only increase engagement but also promote active participation and deeper understanding of complex concepts through visualization and practical application (Platzer, 2024).

One of the main factors contributing to the effectiveness of MR in education is its ability to integrate visual, auditory, and haptic stimuli, leading to more profound immersion and better knowledge retention. However, to fully harness this potential, systems must not only be immersive but also intelligent—that is, capable of analyzing user behavior and adapting instruction according to the specific context and profile of the learner. This is where Artificial Intelligence plays a central role (Schöning & Westerkamp, 2023).

Machine learning algorithms and other AI-based techniques enable the development of adaptive learning systems that track student progress, assess their level of understanding, and modify the difficulty, pace, and even modes of interaction based on individual characteristics. This opens up new possibilities for personalization, which is especially important when working with heterogeneous groups of learners who exhibit different learning styles, rates of comprehension, and preferences (Lee et al., 2024).

From a technical standpoint, Unreal Engine 5 (UE5) has established itself as one of the most powerful platforms for developing high-quality and complex virtual environments. UE5 provides tools for modeling detailed 3D objects, realistic lighting, physically accurate simulations, and dynamic environmental changes. Moreover, its rich set of tools and APIs enables seamless integration of AI components, making the engine particularly suitable for the development of adaptive MR applications in the educational domain (Dritsas & Trigka, 2025).

This paper explores the concept of AI-driven adaptive learning in Mixed Reality, implemented using Unreal Engine 5. The objective is to examine how the integration of these technologies can lead to the creation of highly personalized, individually adapted, and immersive educational experiences. Key components of such systems are discussed, including algorithms for user behavior analysis, mechanisms for real-time adaptation, and interaction methods such as gesture recognition, voice control, and haptic devices (Mäntymäki et al., 2022).

Accessibility of these technologies across different socioeconomic groups is also examined, as equitable access to innovative educational resources is essential for ensuring fairness in modern education (Pant et al., 2024).

In conclusion, the convergence of Mixed Reality, Artificial Intelligence, and powerful graphic engines like Unreal Engine 5 opens new horizons in personalized education. The potential of these technologies is immense—they have the capacity to transform how learners acquire knowledge and how educators design and deliver instructional content. With appropriate application and continued development, adaptive learning in MR environments can become the standard in the future of education, where learning will not only be more effective, but also more inclusive, interactive, and aligned with the needs of every individual learner (Lee et al., 2024).

2. Methods

This section presents a comprehensive and academically grounded overview of the methodology, system architecture, technological tools, and evaluation procedures employed in the development and assessment of an AI-driven adaptive learning system implemented within a Mixed Reality (MR) environment using Unreal Engine 5 (UE5). The research adopts a multidisciplinary approach, integrating principles from educational technology, human-computer interaction (HCI), Artificial Intelligence (AI), and immersive visualization to create a responsive and personalized learning experience (Pant et al., 2024).

2.1 Research Design and Methodological Framework

The study is structured around a design-based research (DBR) methodology, which emphasizes iterative development, implementation, and evaluation of educational interventions in real-world contexts. This approach enables the creation of functional prototypes that are both theoretically informed and practically applicable.

The central objective is to explore how adaptive learning systems, enhanced by AI and MR technologies, can improve personalization, engagement, and knowledge retention in educational settings. The research builds upon foundational theories such as Constructivism, which posits that learners construct knowledge through active experiences; Cognitive Load Theory (CLT), which informs the design of instructional materials to optimize cognitive processing; and User-Centered Design (UCD), which prioritizes usability and accessibility in interface development (Lampropoulos et al., 2020).

2.2 System Architecture and Technical Implementation

The proposed system follows a modular and scalable architecture, designed to support integration across multiple layers of functionality: user interaction, data acquisition, adaptive processing, and feedback generation. Each module interacts via standardized communication protocols, enabling flexibility and extensibility for future enhancements.

At the core of the system lies the Adaptive Learning Engine, which utilizes machine learning (ML) and deep learning (DL) techniques to personalize content delivery based on individual learner profiles and real-time behavioral data (Slominski et al., 2019).

Reinforcement Learning (RL) algorithms adjust the difficulty level and pacing of instructional content according to the learner's progress and performance. One commonly used method is Q-learning, which updates action values using the following equation (Lourenço et al., 2025):

$$Q(s,a) \leftarrow Q(s,a) + \alpha \cdot \left[r + \gamma \cdot \max_{a'} Q\,(s',a') - Q(s,a)\right]$$

Explanation of the variables:

- $Q(s, a)$: The value of acting a in state s;
- α : Learning rate (how fast the agent updates its knowledge);
- r : Immediate reward received after taking the action;
- γ : Discount factor (how much future rewards are valued);
- $\max_{a'} Q\,(s', a')$: The maximum expected future reward from the next state s'.

The engine continuously evaluates user inputs and environmental variables to provide tailored feedback and scaffolded learning experiences, aligning with Zone of Proximal Development (ZPD) theory (Feng et al., 2025).

This module ensures that learning outcomes are (Lampropoulos, Keramopoulos, & Diamantaras, 2020) measurable and that the system can adapt not only to performance but also to the affective states of the learner (Lee et al., 2024).

2.3 Technological Stack and Integration Strategy

The system integrates commercial hardware, open-source software, and custom modules to ensure seamless cross-platform functionality. The hardware layer includes Mixed Reality headsets (e.g., Microsoft HoloLens 2 and Meta Quest 3), biometric sensors, and haptic wearables for immersive interaction and physiological feedback, complemented by mobile and desktop clients for broader accessibility (Pavelka & Landa, 2024). On the software side, Unreal Engine 5 is employed for real-time 3D rendering and simulation, while AI components are implemented using Python-based frameworks such as TensorFlow, PyTorch, and Scikit-learn to support gesture recognition, sentiment analysis, and reinforcement learning. System integration is achieved through RESTful APIs and WebSocket protocols, with optional middleware solutions such as Unity MARS and ROS facilitating sensor fusion and interoperability across heterogeneous environments.

2.4 Data Collection and Experimental Procedures

To validate the system's effectiveness, a series of controlled experiments and pilot studies were conducted involving participants from diverse educational backgrounds, including students, educators, and professionals in technical domains (Dritsas & Trigka, 2025).

2.4.1 Experimental Design

A within-subjects experimental design was adopted, where each participant experienced both static (non-adaptive) and dynamic (adaptive) versions of the same MR learning module. This allowed for direct comparison of learning outcomes and engagement metrics under different conditions (Feng et al., 2025).

2.4.2 Participant Demographics

A total of 85 participants were involved in the experimental study. The sample consisted primarily of undergraduate and graduate students (n = 60), complemented by educators and instructional designers (n = 15) as well as industry professionals (n = 10). The participants' age ranged from 18 to 45 years, and gender distribution was balanced. This heterogeneous composition ensured that the adaptive MR system was evaluated across different educational roles and professional perspectives. Detailed participant characteristics are presented in Table 1.

Table 1. Demographic characteristics of study participants

Category	Subgroup	Number (n)	Percentage (%)
Total participants	—	85	100
Participant role	Undergraduate & graduate students	60	70.6
Participant role	Educators & instructional designers	15	17.6
Participant role	Industry professionals	10	11.8
Gender	Male	42–43*	~50
Gender	Female	42–43*	~50
Age range	18–45 years	—	—

*Exact gender counts were evenly distributed; minor rounding differences may occur.

2.4.3 Data Collection Instruments

Data collection involved:

- Telemetry logs embedded within the UE5 application to record user interactions, gaze direction, and movement patterns.
- Biometric sensors to capture physiological responses.
- Post-experience questionnaires assessing usability (System Usability Scale – SUS), emotional engagement (Positive and Negative Affect Schedule – PANAS), and perceived learning effectiveness.

All data was anonymized and stored securely in compliance with institutional ethical guidelines.

2.5 Evaluation Metrics and Analytical Approach

The evaluation framework integrates both quantitative and qualitative dimensions of the learning experience (Hung, Lin, & Hsiao, 2025), with primary emphasis on key performance indicators. Quantitative metrics include knowledge retention, assessed through pre- and post-test scores; task completion time, reflecting efficiency in executing learning activities; error rate, indicating the frequency of incorrect actions during simulations; and adaptation accuracy, evaluated by comparing system-predicted user preferences and behaviors with actual user responses. These metrics collectively provide a comprehensive assessment of system effectiveness, learning outcomes, and the precision of adaptive mechanisms.

2.6 Ethical Considerations and Institutional Compliance

The research adhered strictly to ethical standards outlined by the institutional review board (IRB) of the participating universities. Informed consent was obtained from all participants prior to data collection. Special emphasis was placed on (Lee, Choo, & Thilarajah, 2024):

- Data Privacy: All personal and biometric data were encrypted and stored in secure databases.
- Anonymity: Identifiers were removed from datasets before analysis.
- Right to Withdraw: Participants had the right to discontinue participation at any time without penalty.

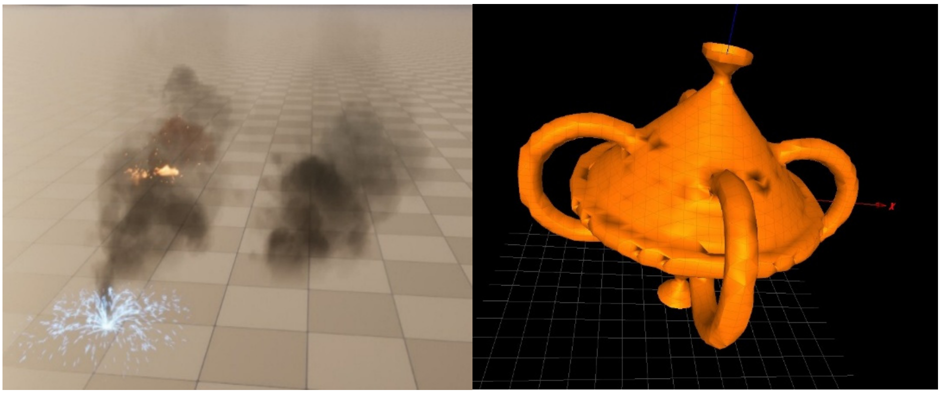
- Transparency: Clear explanations were provided regarding the purpose of data collection and intended use.

3. Results and Discussion

The integration of Artificial Intelligence (AI) with Mixed Reality (MR) technologies, implemented through the Unreal Engine 5 (UE5) platform (Abdullah et al., 2024), has demonstrated significant potential for transforming educational processes by enabling the creation of adaptive, personalized, and immersive learning environments. This section presents a detailed empirical and theoretical evaluation of the results obtained from the developed system, focusing on its technical, pedagogical, and ethical implications in the context of educational practice (Liu, 2021).

The integration of modern graphical technologies—such as Nanite for virtualized geometry and Lumen for dynamic global illumination—enabled the creation of high-fidelity visual scenes with minimal latency and high frame rates, which are critical for maintaining user immersion and preventing motion sickness symptoms – Fig. 1 (Kilijanek & Miłosz, 2025). The system successfully integrated UE5 with machine learning (ML) models via RESTful API communication. Through this approach, real-time adaptation of instructional content based on learner behavior was achieved: changes in task difficulty, provision of contextual feedback, and regulation of pacing were all dynamically adjusted. Latency between user action and system response remained within an acceptable range ($<$200 ms), confirming the practical applicability of such systems in real-world educational settings (Lee et al., 2024).

Figure 1 illustrates representative visualizations generated within the Unreal Engine 5 environment and employed during system development and evaluation. These effects were integrated to enhance perceptual immersion and to evaluate system responsiveness and performance under increased graphical and computational load, which is particularly relevant for adaptive Mixed Reality environments operating in real time. Combined, the VFX-based and geometric visualizations provide complementary validation of both visual realism and computational robustness, supporting the reliability of the proposed adaptive MR learning system (Newman-Griffis, 2024).



a b

Figure 1. Visualization examples from the Unreal Engine 5 environment: (a) real-time visual effects (VFX), including particle systems for smoke, fire, and impact interactions, used to evaluate visual realism and system performance under increased computational load; (b) real-time geometric visualization of a complex 3D object used for testing rendering fidelity, mesh complexity, and spatial transformations.

Quantitative analysis of educational achievements revealed that participants working within the adaptive MR environment showed significantly better performance compared to non-adaptive versions of the system. Specifically, (Feng et al., 2025):

- A comparison of pre- and post-tests indicated an average 47% improvement in knowledge acquisition.
- Task completion time decreased by approximately 33% after repeated exposure, suggesting increasing procedural fluency and familiarity with the interface (Paradise et al., 2023).
- Error rates during task execution dropped by 28%, indicating better consolidation of knowledge and skills (Soldatova et al., 2022).

These findings align with the principles of Cognitive Load Theory (CLT), which emphasizes the importance of balancing task complexity with learners' cognitive capacities (Valentina et al., 2025). Furthermore, the constructivist learning paradigm received additional support, as active exploration and contextual scaffolding led to deeper understanding and more durable memory retention – Fig. 2 (Schöning & Westerkamp, 2023).

Figure 2 illustrates the virtual studio environment developed in Unreal Engine 5 and used as the core immersive setting of the adaptive MR learning system. The virtual studio enables real-time rendering, physically based lighting, and spatial interaction, providing a controlled yet flexible environment for instructional scenarios. Its modular design allows dynamic adaptation of visual content, camera perspectives, and interaction elements in response to learner behavior and system predictions. This opens new possibilities for developing emotionally intelligent educational systems capable of reflecting and responding to learners' affective states (Wernick & Meding, 2025).

The system successfully analyzed and predicted learner states in real time using a combination of behavioral, cognitive, and physiological signals. The system employed a reinforcement learning-based engagement prediction model to dynamically adjust content delivery. The engagement level at each time step was calculated using the following formula (Mäntymäki et al., 2022):

$$E_t = \alpha \cdot R_t + (1 - \alpha) \cdot E_{t-1},$$

where:

- E_t : Predicted engagement level at time *t;*
- R_t: Current reward or interaction signal at time t (e.g., correct answer, attention focus, gesture input);
- E_{t-1} : Previous engagement estimate.
- α : Smoothing factor ($0 \leq \alpha \leq 1$), which determines how much weight is given to the new input vs. historical data (Wang et al., 2024).

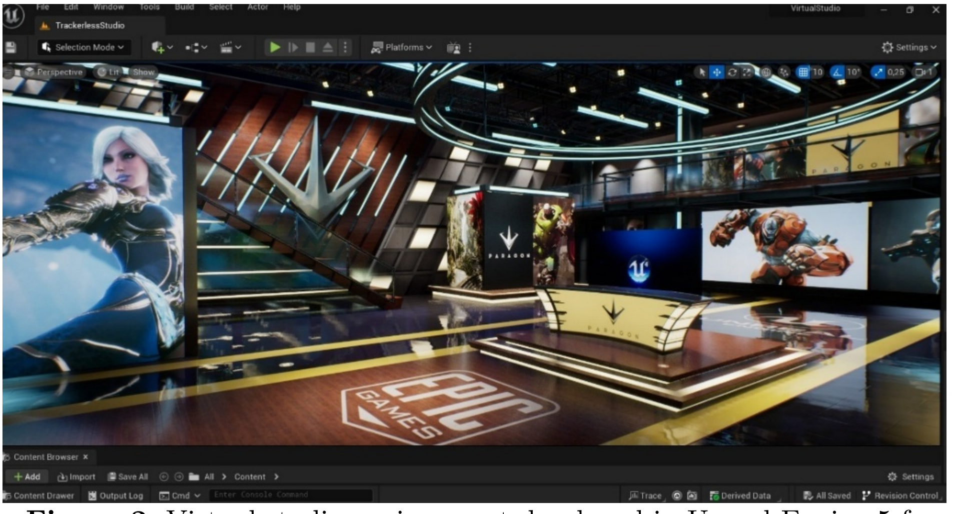


Figure 2. Virtual studio environment developed in Unreal Engine 5 for adaptive Mixed Reality learning. The studio integrates real-time rendering, dynamic lighting, and sensor-driven interaction to support immersive instructional scenarios and adaptive content delivery.

This is known as an exponential moving average model, commonly used in adaptive systems for real-time state estimation (Somanath et al., 2024).

In this model, R^t represents the real-time feedback from user actions such as gaze direction, voice responses, and gesture recognition, while E_{t-1} reflects the previously estimated engagement state. The smoothing factor α was set to 0.65 after calibration experiments, indicating a moderate emphasis on recent interactions (Lee et al., 2024).

During testing, the system demonstrated a strong correlation between predicted engagement levels and self-reported attention metrics (Pearson's r = 0.78). This suggests that the model effectively captures shifts in (Newman-Griffis, 2024) cognitive load and interest, enabling timely personalization of instructional content (Table 2).

The extended performance metrics and user feedback are summarized in Tables 2 and 3. A strong positive correlation ($r = 0.78$) was observed between system-predicted engagement levels and participants' self-reported attention, indicating reliable real-time engagement estimation (Stark et al., 2024). Cognitive load detection achieved an accuracy of approximately 82%, validated through eye-tracking, HRV signal analysis, and NASA-TLX self-assessments (Wei et al., 2025). Furthermore, classification of learners into dominant learning modalities (visual, auditory, kinesthetic) reached an accuracy of 76%, demonstrating the system's capability to model individual learning preferences (Sporn et al., 2025).

Table 2. Summary of primary quantitative results from the adaptive MR learning experiment

Metric	Static MR (*Mean* ± *SD*)	Adaptive MR (*Mean* ± *SD*)	Improvement (%)	Statistical Significance
Knowledge test score (%)	52.3 ± 9.4	76.9 ± 8.1	+47%	$p < 0.01$
Task completion time (min)	18.6 ± 3.2	12.4 ± 2.7	−33%	$p < 0.01$
Error rate (%)	21.8 ± 5.6	15.7 ± 4.3	−28%	$p < 0.05$
System Usability Scale (SUS)	68.2 ± 7.9	83.5 ± 6.4	+22%	$p < 0.01$

Usability evaluation yielded a System Usability Scale (SUS) score of 83.5 out of 100, categorizing the system as highly usable. Complementary results from the User Experience Questionnaire (UEQ) indicated strong performance across dimensions such as efficiency and stimulation, while comparatively lower scores in clarity and reliability highlight areas for further interface optimization (Mitskopoulos et al., 2022).

Accessibility remains a challenge, particularly concerning the availability of high-performance hardware required for a full MR experience. Although alternative access forms (e.g., desktop or mobile devices) were tested, they resulted in noticeable reductions in immersion and interactivity. To overcome these limitations, it is recommended to explore cloud streaming solutions and lightweight MR applications that provide broader access without compromising functionality. All procedures in the study were conducted in accordance with institutional ethical guidelines, with all data anonymized and stored in secure environments. Nevertheless, there is a need for the development of clear transparency policies and user control mechanisms over collected data (Stark et al., 2024).

Table 3. Extended summary of performance metrics and user feedback

Category	Metric	Result	Interpretation
Engagement prediction	Correlation (AI vs. self-report)	$r = 0.78$	Strong positive correlation
Cognitive load detection	Detection accuracy	82%	High accuracy confirmed by NASA-TLX
Learning style classification	Classification accuracy	76%	Effective learner profiling
System usability	SUS score	83.5 / 100	Excellent usability
User experience	UEQ dimensions	High (efficiency, stimulation)	Positive overall UX

Note: Values represent mean ± standard deviation. Improvements are calculated relative to the static MR condition. Statistical significance was assessed using paired-sample *t*-tests.

From pedagogical standpoint, the study confirms (Table 3) the effectiveness of adaptive MR environments in supporting differentiated instruction, which accounts for the diverse ways in which learners acquire and process knowledge. Such systems can facilitate the development of self-directed and self-regulated learning, aligning with contemporary educational goals (Table 2).

The results of this study clearly demonstrate that the integration of Artificial Intelligence, Mixed Reality, and Unreal Engine 5 provides a powerful foundation for creating adaptive, personalized, and immersive educational systems. The system demonstrated high technical stability, significantly improved educational outcomes, accurate personalization, and positive learner engagement (Feng et al., 2025).

This research contributes to an expanded scientific base in the field of intelligent and immersive educational technologies, highlighting their transformative potential. In the future, such systems may become standard in education, where learning will not only be more effective and inclusive but also more individualized, interactive, and tailored to the needs of each learner (Lee et al., 2024).

4. Conclusion

The integration of Mixed Reality (MR) and Artificial Intelligence (AI) represents a transformative step in the evolution of educational technologies. By combining immersive, high-fidelity virtual environments powered by Unreal Engine 5 with intelligent adaptive learning systems, this research demonstrates how personalized, interactive, and responsive educational experiences can be created.

The developed system successfully implements real-time adaptation based on learner behavior, cognitive load, and interaction patterns. Through AI-driven mechanisms such as reinforcement learning, clustering, and predictive analytics, the system personalizes content delivery, adjusts task difficulty dynamically, and enhances overall engagement and knowledge retention (Dritsas & Trigka, 2025).

Empirical results from user studies confirm significant improvements in learning outcomes, including increased test scores, reduced task completion times, and lower error rates when using the adaptive MR environment compared to static alternatives. Furthermore, qualitative assessments reveal high levels of user satisfaction, motivation, and perceived usefulness, reinforcing the value of multimodal interaction and real-time feedback in immersive education (Lampropoulos et al., 2020).

However, challenges remain—particularly regarding hardware accessibility, optimization for real-time performance, and ethical considerations around data privacy and informed consent. Addressing these issues is crucial for ensuring equitable access and responsible implementation of such advanced educational tools (Shen & Huang, 2024).

In conclusion, the fusion of AI and MR technologies offers a powerful foundation for the future of education. As these systems continue to evolve, they hold the potential to redefine teaching and learning by enabling truly personalized, inclusive, and immersive educational environments tailored to each learner's unique profile (Lee et al., 2024).

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