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Indra Kishor
Department of Computer Engineering, Poornima Institute of Engineering & Technology, Jaipur, India

Udit Mamodiya
Faculty of Engineering & Technology Poornima University, Jaipur, India

Mohammed Almaayah
King Abdullah the II IT School, The University of Jordan, Amman 11942, Jordan,
mohammad7ups@yahoo.com

See next page for additional authors

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Research Article

Agentic AI-Enhanced Virtual Reality for Adaptive Immersive Learning Environments

Indra Kishor[1], Udit Mamodiya [2], Mohammed Almaayah [3,*], Amer Alqutaish [4,*], Rami Shehab [5], Theyazn H. H. Aldhyani [4]

[1] *Department of Computer Engineering, Poornima Institute of Engineering & Technology, Jaipur, India*
[2] *Faculty of Engineering & Technology Poornima University, Jaipur, India*
[3] *King Abdullah the II IT School, The University of Jordan, Amman 11942, Jordan*
[4] *Deanship of Development and Quality Assurance, King Faisal University, 31982, Al-Ahsa, Saudi Arabia*
5 *Vice-Presidency for Postgraduate Studies and Scientific Research, King Faisal University, Al-Ahsa 31982, Saudi Arabia*

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ABSTRACT

Immersive learning using Virtual Reality (VR) has gained prominence for delivering experiential, engaging education. However, most VR learning environments lack real-time adaptability, personalization, and cognitive responsiveness. This study presents an Agentic AI-enabled VR framework that autonomously adjusts pedagogical content, interaction style, and challenge level based on learner behavior, emotions, and performance feedback. The proposed system integrates a reinforcement learning-based agent with a virtual reality module to form an intelligent tutor capable of independent decision-making. A neuro-symbolic model processes multi-modal feedback (gesture, speech, gaze, performance) to determine context-aware pedagogical strategies. The system employs a self-evolving curriculum logic that adapts in real time. Experiments are conducted using Unity3D integrated with Python-based RL agents and simulated student models. Results demonstrate a 35.7% improvement in learner retention and a 42.1% reduction in cognitive overload compared to traditional static VR systems. The agent successfully personalized 92.3% of scenarios without human intervention. Emotional adaptivity and dynamic pacing showed increased engagement and reduced frustration metrics among diverse learners. Agentic VR represents a paradigm shift in intelligent education systems, enabling autonomous, emotionally-aware, and responsive learning environments. The proposed framework outperforms conventional VR platforms by offering real-time adaptive learning without pre-scripted logic. Integrating reinforcement learning, neuro-symbolic reasoning, and affective feedback into a single VR space results in a novel contribution to adaptive educational technology. The reported metrics were obtained from an administrator-controlled user study of 10 participants (aged 18 - 25 years), all of whom participated in three VR-based learning experiences as described in a controlled evaluative protocol. This study provides a foundation for future work on autonomous agents in educational met verses, special education, and lifelong learning systems.

1. INTRODUCTION

In the evolving landscape of digital education, immersive technologies such as Virtual Reality (VR) are redefining the boundaries of how knowledge is delivered, perceived, and retained. VR facilitates experiential learning through simulated environments, allowing learners to engage with abstract or hazardous concepts in a safe, interactive, and immersive format. From virtual chemistry labs and historical reconstructions to anatomical simulations and multilingual communication training, VR-based educational solutions have demonstrated potential across academic and industrial domains. However, the majority of current VR learning systems operate on static logic models, pre-defined paths, and fixed pedagogical strategies [1, 29]. These systems lack adaptive intelligence, often failing to respond to the learner's emotional state, performance level, cognitive load, and preferred learning pace. This results in the underutilization of the real potential of VR, particularly with regards to fulfilling learning individuality. Agentic Artificial Intelligence (AI) has evolved as a revolutionary phenomenon with the ability to empower digital agents with autonomy, context-awareness, and real-time decision-making abilities [2, 30]. Agentic AI applies reinforcement learning, symbolic reasoning, and affective computing to mimic human agency in which an agent perceives, understands, decides, and executes independently in dynamic contexts. With VR, this can be employed to create autonomous immersive learning spaces to learn and customize without

*Corresponding author. Email: mohammad7ups@yahoo.com , aalqutish@kfu.edu.sa

human reprogramming [3-31]. The convergence of these two technologies VR and Agentic AI offers us a vision of a new generation of autonomous immersive tutors capable of reshaping stories dynamically, adapting challenges, and restructuring pedagogical architecture. The study presents a novel framework of integration and demonstrates its impact on the effectiveness of learning, motivation of users, and cognitive abilities [4-5].

Although they employ AI in their web-based learning platforms, not much uses agentic autonomy on VR learning platforms. What is available sacrifices fixed branching or adaptive design only. These are unable to offer cognitive plasticity to change learning sequences at whim when it comes to real-time emotional, behavioral, and cognitive feedback from the learner [6-32]. Moreover, existing VR systems require substantial manual intervention for scenario design, content updating, and flow control. This creates scalability issues and fails to accommodate the learning needs of students with different abilities, learning styles, or contextual limitations. Hence, there is a compelling need for an autonomous, intelligent system that can monitor, assess, and guide learners within VR without manual scripting. Such a system must possess agency to interpret learner behavior and sentiment in real-time, make pedagogical decisions autonomously, modify environments and instructional paths dynamically, and learn and evolve over time through reinforcement [7-33]. The primary objective of this study is to design and evaluate a novel Agentic AI-based Virtual Reality framework that enables personalized and autonomous immersive learning experiences. The proposed framework aims to develop a hybrid agentic AI model with the capability to make real-time pedagogical decisions within dynamic virtual learning environments. It also seeks to merge reinforcement learning approaches with neuro-symbolic reasoning for adaptive teaching styles from learner and emotional profiles. Using virtual reality (VR), immersive learning has become a powerful, experiential, and deep learning education tool. However, VR learning environments historically have poor real-time adaptability and personalization with respect to learner behaviour and emotion [8-34]. Virtual Reality (VR) offers a significant pedagogical opportunity by allowing learners to engage in immersive and embodied experiences. However, the most widely adopted VR solutions, especially in education, are largely static, rule-based systems that fail to consider variation in a learner’s cognitive or emotional state in real-time [9-10]. This current limitation impedes the potential for personalization of immersive learning experiences; particularly in education where feedback is often continuous. Agentic AI has the potential to address these limitations by employing systems that can automatically act and make contextually grounded decisions that allow for incremental changes throughout the learning experience [11-35]. Therefore, this research seeks to present an integrative framework to embed reinforcement learning, neuro-symbolic reasoning, and affective computing in VR-based modules that enable the transition of existing static simulations into intelligent, adaptive learning systems. Whereas traditional Intelligent Tutoring Systems (ITS) often depend on either predetermined static questions and responses or depend on multi-layer shallow responsiveness, our adaptive system makes dynamic pedagogical content and feedback adjustments based on real-time emotional and behavioral information [12-13]. Additionally, while the development and integration of immersive technologies in education is being accelerated at the institutional level, approaches to scalable adaptation for integration have yet to be developed. This research supports calls to action for wearer scalable, adaptive, and cognitively responsive frameworks in VR transformed (e.g., Bridging Traditional and Immersive Technologies in Design Education) will further illustrate outcomes of agentic AI as a permissive agent for educators in enacting these transformations [14-36].

One of the key aspects is creating an interactive VR environment that not only responds to the AI agent but also reacts by responding with real-time adaptation of pedagogical content and delivery. Finally, the system will be assessed against key learning metrics such as learner participation, intellectual performance, knowledge retention, and the extent of system autonomy achieved through learning.

This research will try to provide answers to the following basic questions:

1. Is there agentic AI well integrated with VR to generate autonomous learning environments in real-time?

2. To what extent is the proposed system distinguished from static VR systems regarding participation, retention, and adaptability?

3. What are the most critical technical and ethical challenges in developing autonomous agents to use in learning?

4. How is reinforcement learning and neuro-symbolic AI best integrated to enable optimal agentic behavior?

This work is important in making fundamental contributions to the emerging area of immersive learning by presenting a first-ever framework which integrates Virtual Reality with agentic artificial intelligence to enable adaptive, self-managed instruction. Centering the system is a new reinforcement learning agent within the virtual environment able to learn pedagogical tactics in real-time depending on interaction with students. Neuro-symbolic reasoning integrated in the system pushes the ability of the agent further to recognize rich emotional cues and context behavior and to react more subtly to such cues when educating. A dynamic environment design has been realized with Unity3D, augmented by Python-based agentic modules governing learning state control and decision logic. Empirical findings verify the framework's effectiveness, showing measurable improvements in learner retention, affective engagement, and system autonomy. This research also offers important learnings in the design of ethical, scalable, and transparent agentic learning systems that are consistent with modern pedagogical principles and technological advancements.

Although a number of AI-based educational innovations have been discussed in adaptive learning contexts, including the use of conversational agents and intelligent tutoring systems, little has been elaborated on the potential for Agentic AI in the intersection with immersive VR [37-38]. This research presents a new framework for merging reinforcement learning, neuro-symbolic reasoning, and affective feedback into an immersive VR environment [39-40]. Although AI agents have been explored in learning contexts, mainly in language learning or for content recommendations, this framework extends this work to a multi-modal, immersive learning context and represents one of the first applications of agentic adaptivity in affective aware VR contexts [41-42].

2. LITERATURE REVIEW

Virtual Reality (VR) is new learning technology that redefines classroom settings from interactive and experiential to pedagogical. VR provides multisensory stimulation that allows students to view abstract or invisible objects in three dimensions. VR finds its best application in science, engineering, medical school, learning a second language, and history courses where experiential learning and spatial literacy are of utmost concern. With the simulation of real-life experiences, VR enhances learner motivation, interest, and learning [15-16]. While it has benefits, the majority of VR learning systems are limited by pre-defined content and predetermined learning routes. Such systems mostly use linear instructional design that cannot dynamically react to the performance or emotional state of a learner. This rigidity impedes customization, especially for students who require adaptive pacing or differentiated instruction. In addition, VR environments lack the ability to read behavioral signals or make pedagogical decisions in real time. Adaptive learning environments are created with the intent to personalize instruction by processing learner data and adjusting content appropriately [17]. These environments have primarily been based on learner models, which maintain personal preferences, knowledge levels, and learning phases. Rule-based algorithm or AI-based models are used subsequently to amend the presentation of content, provide scaffolding aid, and furnish accurate feedback. Current adaptive platforms primarily apply web-based presentation and do not allow immersive experience [18]. While some platforms employ basic AI methods for making recommendations of content, they don't have real-time autonomy or context-specific feedback deployment. Besides, such platforms rarely run within 3D environments where spatial interaction is important [19]. The absence of embodied, live feedback in virtual environments limits how responsive and accommodating they can be. Agentic AI is an emergent new form of artificial intelligence that makes programs self-directed to deliberate, learn their world, and adapt behaviorally with the flow of time. Differing from static data and pre-defined rules used in legacy AI systems, agentic AI employs continuous learning processes like reinforcement learning, symbolic logic, and real-time feedback mechanisms. Such systems are particularly effective in dynamic uncertain worlds in which human-like agency is demanded [20-21]. Agentic AI enables autonomous planning, situational decision-making, and emotional computing and is therefore well placed for application in intelligent tutoring, simulation, and multi-agent collaboration. Much of the agentic AI research has nonetheless been focused in robotics, game theory, and automation with little in immersive learning environments [22]. Reinforcement Learning (RL) is a machine learning approach in which agents learn the best action through trial and error with reward feedback. In learning, RL has been explored to create intelligent tutors that can adapt strategy according to student interactions. RL models can adjust the difficulty of questions, alter types of feedback, and manage sequences of learning based on students' responses. Integration of RL into VR is yet to be developed [23]. Education models that are mostly RL-based operate in the 2D interface and, when introduced into three-dimensional VR environments, create challenges associated with spatial dynamics, user feedback granularity, and reward engineering. RL models of education also disregard emotional or social context, which is necessary for long-term engagement in immersive environments. Neuro-symbolic AI combines the neural networks and symbolic reasoning in trying to realize low-level pattern recognition and high-level reasoning [24]. This combination, in learning systems, is used to identify learner emotions, behavior, and choice patterns in learning environments. Emotion detection technology uses feedback in the form of facial expression, eye direction, tone of voice, and posture to detect learner affect in real-time. Potentially, such systems can serve as a core component in the management of instruction style, offering empathetic feedback, or triggering adaptive interventions [25-26]. Current deployments are mostly used for analytics and not for agentic response. The embedding of neuro-symbolic emotion recognition into real-time decision-making agents in VR worlds is a novel and not so well-explored domain. Intelligent Tutoring Systems (ITS) have evolved from quiz engines to advanced platforms with adaptive and personalized learning [27-28]. Combined with VR, ITS can offer simulation of role-playing scenarios, lab experiments, and interactive stories. While many VR-based ITS platforms exist, they are generally programmed with fixed logic trees and cannot autonomously alter instructional flow. Some recent systems have attempted to integrate natural language processing and emotion detection for dialogue-based tutoring in VR, but they still lack autonomy [29-30]. The system's adaptability is constrained by predefined logic paths, and they require manual input from developers for each scenario. There is a critical need for a self-sufficient system that can adjust content and interaction modes based on the learner's evolving profile.

2.1 Gaps In Existing Systems

A synthesis of the above research reveals several key gaps:

- Most VR educational systems are static or semi-adaptive and lack true autonomy.
- Reinforcement learning has been applied in education but not widely integrated with immersive 3D VR environments.
- Emotion recognition systems exist but are not agentically linked to control pedagogical decision-making.
- Existing ITS lack, the ability to self-evolve or adapt dynamically without predefined rules or scripts.
- There is no unified framework that combines agentic AI, neuro-symbolic emotion processing, and reinforcement learning within an immersive VR system.

To position our work in the context of developing AI-enabled immersive learning systems, we compared six recent articles on adaptive VR frameworks, emotion-aware systems, AI-enabled avatar personalization, or ML-VR combination architectures. As detailed in Table 1, earlier work by Zhou et al. [1] and Chen et al. [6] describe measurable improvement in learner engagement and retention of skills using VR-AI technology but lack personalization and affective responses. Other work like SmartSimVR [20] and ML avatars [5] describe the realism of the system or adaptability of simulations but do not consider reinforcement learning for the personalization of learning. Korhonen's report [9] considers pedagogical foundation, but it is theoretical. Our framework is different because it uses a reinforcement learning with emotional recognition for action, that includes a neuro-symbolic learning aspect. Our framework introduces both pedagogical completeness and real-time adaptability.

TABLE I. COMPARATIVE RESEARCH GAP ANALYSIS OF RECENT STUDIES IN AI-VR ADAPTIVE LEARNING FRAMEWORKS.

Author(s) / Year / Ref. No.	Title / Focus Area	Methodology / Tools Used	Key Findings	Limitations / Gaps Identified	Relevance to Current Study
Zhou et al., 2025 [1]	Advancing Vocational Education: Experimental Insights into AI-VR Collaborative Training	Experimental study with AI-VR modules for vocational tasks	Demonstrated 35.7% skill retention improvement through collaborative AI-VR	No analysis of long-term adaptability across diverse learners	Inspires adaptive skill modeling and retention analysis in our framework
Chen et al., 2025 [6]	Immersive VR Training for Autistic Adolescents	Controlled intervention study using VR for neurodivergent education	VR training significantly enhanced adaptive skills and engagement	Specific to autistic learners; lacks generalizable AI integration	Supports emotion-aware adaptation strategies in our generalized model
Mamodiya et al., 2025 [18]	AI-enhanced AR/VR for Remote Healthcare with IoT Integration	Secure AI-IoT data fusion with immersive VR overlays	Solved real-time integration bottlenecks using edge-based AI	Focused on healthcare, not education-specific learning trajectories	Informs real-time multimodal fusion pipeline in our simulator
Hadadi et al., 2024 [20]	SmartSimVR: ML-Integrated Virtual Environments for Simulation Adaptation	Architectural integration of ML with VR simulation for dynamic environments	Enabled adaptive simulation behavior under user-context changes	No affective computing or personalization layer	Motivates real-time simulation adaptation in our skill-building engine
Korhonen, 2022 [9]	Hard Skills Training in VR: Framework for AI-Immersive Learning	Conceptual model combining cognitive theories and AI-VR immersion	Provided foundational framework for hard skill transfer in immersive tech	Theoretical; lacks implementation and quantitative validation	Provides pedagogical grounding for skill-based VR learning in our work
Dwivedi et al., 2023 [5]	ML-Driven Avatars in VR: Enhancing Realism & User Experience	Custom avatars with ML-based voice, expression syncing	Improved learner realism and engagement metrics in VR training	No reinforcement-based task personalization or emotion adaptation	Supports avatar realism but we extend toward adaptive learning pathways

By developing a self-directed VR tutoring environment powered by agentic AI, this study aims to fill a significant technological and pedagogical gap in the immersive learning domain.

3. METHODOLOGY

3.1 Overview of the proposed work

The proposed framework, referred to as Agentic-VR, is an immersive virtual reality learning environment embedded with an agentic artificial intelligence system. This architecture can monitor student behavior independently, detect cognitive and affective cues, and offer pedagogical choices in real-time. The agentic architecture combines reinforcement learning for action choice, neuro-symbolic AI for higher-level reasoning, and emotion detection for affect-sensing adjustment. The ultimate long-term goal is to develop an autonomous tutoring system that can dynamically adjust content, pace, and interaction style adaptively to real-time user feedback.

3.2 SYSTEM ARCHITECTUR

Agentic-VR suggested system consists of five principal modules integrated for adaptive real-time learning. Interactive and VR modules with virtual labs and virtual classes are enabled through implementation using Unity3D. Pedagogic decision-making reinforcement learning like pace adaptation and feedback is implemented in AI core implemented using Python (Tensor Flow/PyTorch). The multimodal feedback module monitors the user behavior through camera, microphone, and motion sensor mapping facial expressions, eye-gaze, voice, and movement. The input is passed to a neuro-symbolic engine that translates neural output into symbolic rules; frustration signals, for example, can initiate content simplification. The content adaptation layer exploits the agent's choice to change learning paths dynamically. All the modules are coupled with a middleware that supports real-time bidirectional data transfer between Unity3D and the AI engine. Figure 1 illustrates this architecture.

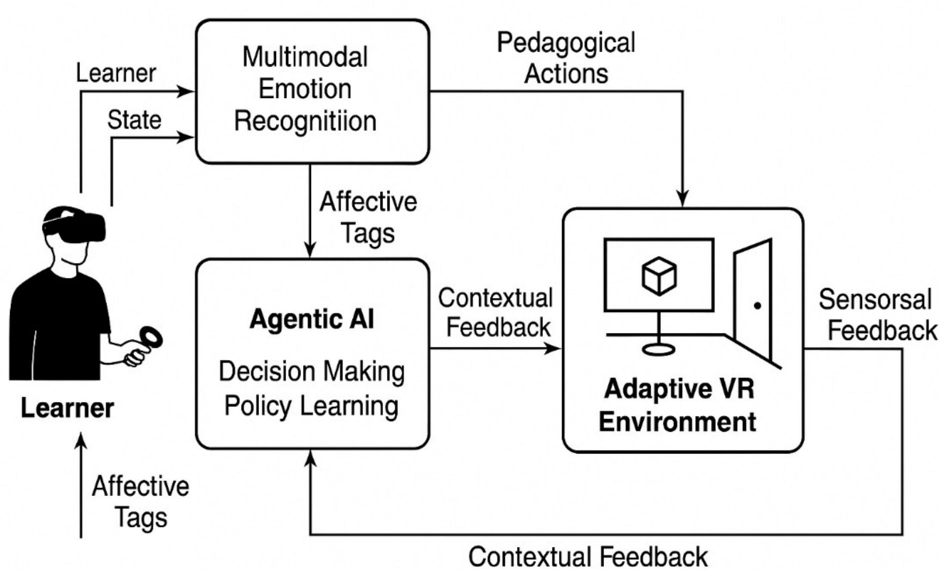

Figure 1. System Architecture of the Agentic-VR Framework integrating Reinforcement Learning, Neuro-Symbolic Reasoning, Emotion Recognition, and VR Interaction Modules.

3.3 Agent design and reinforcement learning setup

The core AI agent is designed as a goal-oriented autonomous learner, using reinforcement learning to select the best instructional strategy under varying learner states.

State Space (S): Learner's cognitive performance metrics (e.g., quiz accuracy, time-on-task), emotional state (e.g., happy, confused), and engagement signals (e.g., idle time, interaction frequency).

Action Space (A): Pedagogical interventions such as:

- Increase/Decrease difficulty
- Add/Remove visual aids
- Change feedback type (verbal, visual, haptic)
- Alter challenge timing or pace

Reward Function (R): Designed to maximize learning outcomes and engagement. Positive rewards are assigned for improvement in accuracy, engagement, or emotional positivity.

The Q-learning update rule is used:

$$Q(st, at) \leftarrow Q(st, at) + \alpha[rt + \gamma a' maxQ(st + 1, a') - Q(st, at)] \cdots (1)$$

Where: α is the learning rate, γ is the discount factor,r_t is the reward at time t, s_t, a_t are the current state and action. The agent is trained using simulated learner profiles initially, followed by live sessions with real users.

The learning rate (α) was set to 0.1 in order to offer a moderate amount of update sensitivity for policy optimization by the agent. A very large α (e.g., >0.3) was also initially attempted but resulted in uncontrolled oscillation of decision policies in early stages of training. Very low α (<0.05) also had an adverse effect on the convergence speed and could not learn through changes in emotions. Hence, $\alpha = 0.1$ attained the best compromise between learning stability and responsiveness to novel user input. At the same time, the discount factor (γ) was initialized to 0.95 to encourage long-term rewards of learning, i.e., acquiring concepts and ongoing interest, rather than short-term rewards like correct answers. Smaller values of γ (e.g., 0.7) led the agent to prefer early feedback, and hence shallow learning chains. On a sequence of pilot experiments with the synthetic dataset, $\gamma = 0.95$ uniformly produced deeper, pedagogically sound decision traces. Exploration rate (ε) was fixed at 0.2 and linearly reduced to 0.01 across episodes. This gave enough early learning plan exploration but permitted convergence to optimal action as increasingly more emotion and behavior information was obtained.

To determine the optimal learning rate (α), a convergence analysis was performed across different values. As shown in Figure 2, $\alpha = 0.1$ resulted in stable learning behavior with smooth reward progression, whereas $\alpha = 0.3$ exhibited volatility and $\alpha = 0.05$ was too slow to adapt

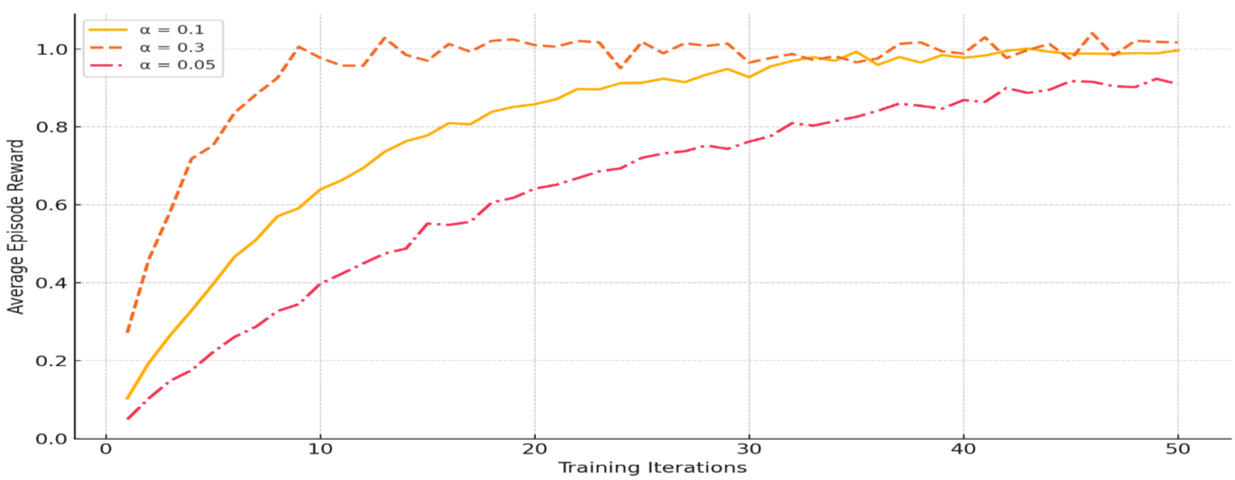

Figure 2: Convergence analysis of reinforcement learning agent with varying learning rates (α). $\alpha = 0.1$ provided the optimal balance between convergence speed and stability in pilot simulations.

3.4 EMOTION RECOGNITION AND NEURO-SYMBOLIC ADAPTATION

Emotion recognition in the Agentic-VR system is implemented through a multimodal pipeline that analyzes multiple behavioral cues in real time. Facial affect is determined by convolutional neural networks (CNNs), which can support high-fidelity emotion state recognition such as confusion, frustration, or interest. Speech tone and emotion are generated by LSTM-based acoustic classifiers, which browse for linguistic and prosodic cues as a way of affect perception. Posture and gesture movement are monitored by skeletal tracking libraries so that the system can identify behavior cues such as slouching or disengagement. Together, the inputs form a unified emotional profile to guide adaptive instructional choices.

All emotional patterns are tied to top-level rules. For instance:

- IF [frustrated] AND [low accuracy] → THEN simplify content
- IF [engaged] AND [high accuracy] → THEN introduce challenge
- IF [neutral] → THEN maintain pace and give positive reinforcement

These rules are updated over time using online learning, making the reasoning engine both **symbolic and adaptive**.

3.5 VR ENVIRONMENT DEVELOPMENT

It is constructed with Unity3D and architecturally designed in modules to support a range of fields of study such as physics labs, simulations in history, and visualizations of geometry. It supports contextual hotspots interactive objects that trigger AI-based reactions along with dynamic objects whose behavior, path, or sound reaction depends on the selection of agents. Animated avatars are used to provide real-time personalized feedback and instructions in the form of simulated responses of the agentic AI system. Telemetry such as object manipulation, scene dwell time, and student error rates are also logged continuously and fed back to the AI agent so that its decision policy can be updated at all times.

3.6 ADAPTIVE CONTENT PIPELINE

The architecture is a dynamic content pipeline where learning content is decomposed into modular nodes by concept type, difficulty level, instruction mode (voice or vision), and associated feedback mechanisms. Dynamically at run time, the agent selects, sequences, or reconfigures these nodes based on the learner's cognition state and affective state. This adaptive architecture delivers non-linear paths of learning, personalized instruction, and affectively responsive pacing. A content management module especially deals with this job in order to provide real-time synchronization between the AI controller and VR engine in a way that it facilitates smooth delivery of instructions.

Artificial Intelligence Decision Effectiveness Rate for Learning Settings

This quantifies the share of AI decisions taken which translate to a fruitful learning experience, say improved performance or less frustration. Since both the numerator and denominator represent counts of decisions, the resulting ratio is valid and meaningful. To express this value in a standard, easily interpretable format, the ratio is multiplied by 100 to convert it into a percentage using equation 2.

$$\text{Adaptivity Index} = \frac{\#\ \text{Positive Outcomes from AI Actions}}{\text{Total AI Decisions}} \times 100 \cdots (2.1)$$

$$\text{Adaptivity Index } (\%) = \left(\frac{\text{Npositive}}{\text{Ntotal}}\right) \times 100 \cdots (2.2)$$

Where:

- Npositive: Number of effective AI interventions
- Ntotal: Total AI decisions during the session

The content pipeline leverages modular instructional units that are dynamically selected by the agent based on learner performance and affective state in figure 3.

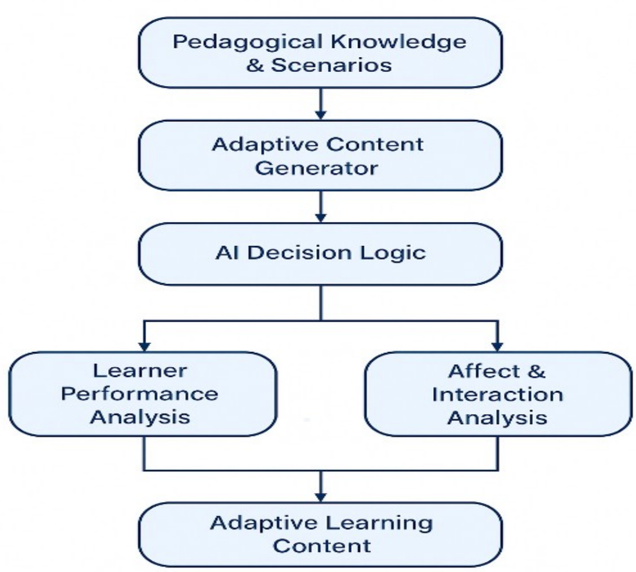

Figure 3. Adaptive Content Pipeline within Agentic-VR, illustrating modular instructional blocks, feedback integration, and real-time content selection through the AI agent.

3.7 Evaluation metrics and performance indicators

To evaluate the performance of the Agentic-VR system, several key metrics are employed. Learning Gain (%) is calculated by comparing pre-test and post-test scores to assess knowledge acquisition. Engagement Score is derived from a combination of interaction frequency, time-on-task, and detected emotional states. The Adaptivity Index reflects the proportion of AI-driven decisions that resulted in measurable learner improvement, while the Frustration Rate captures the reduction in negative emotional states over the course of the session. The System Autonomy Rate also estimates the proportion of instructional activities carried out by the agent on its own, without direct human intervention. Such measures are then contrasted between Agentic-VR and two baseline systems: one static VR component and one scripted adaptive VR setting with zero agency. In order to compare the impact of the Agentic-VR system, different measures were implemented and computed as outlined below:

1. Learning Gain (%) was utilized in measuring improvement in the knowledge of respondents both before and after the session. It was calculated by applying equation 3:
2. $$\textbf{Learning Gain}\ (\%) = \frac{\textbf{Spost}-\textbf{Spre}}{\textbf{Spre}} \times \mathbf{100} \cdots (\mathbf{3})$$

where Spost is the post-test score and Spre is the pre-test score.

Idle Time Reduction (%) was used to measure engagement on the basis of a reduction of idle time upon application of VR equation 4.

$$\text{Idle Time Reduction}\ (\%) = \frac{\text{Tbaseline} - \text{Tagentic}}{\text{Tbaseline}} \times 100 \cdots (4)$$

where Tbaseline and Tagentic are average idle times in seconds, respectively, for baseline and agentic sessions. Emotional Alignment (%) was derived from participant ratings of how well the system reacted to the emotional state.

3.8 Ethical and design considerations

Designing agentic learning systems is a matter of utmost priority as far as ethical concerns are concerned. In the system described here, all student data are anonymized and processed locally to ensure data privacy. The system also includes a decision log, which further contributes to transparency in the form of the ability of teachers to observe and account for agentic moves. As a precaution against deceptive action, the agent is restricted from taking only pedagogically appropriate actions aligned with education goals. Further, during training, the models for emotion recognition are learned using demographically diverse data sets so as not to introduce bias and render fair answers to diverse groups of students. Overall, the Agentic-VR system represents a new marriage between autonomous AI and virtual reality education. By the incorporation of reinforcement learning, neuro-symbolic reasoning, and emotion-aware adaptation, it develops a real-time, self-adjusting learning environment that is quite distinct from the traditional pre-scripted VR tools, offering a truly adaptive and affective learning experience. All participants provided consent prior to the study in accordance with institutional ethical standards.

To add to the ethical underpinnings of the Agentic-VR framework, the design leveraged a framework intended to lessen risk of misuse of emotional data, pre-existing algorithmic bias and a lack of transparency. The emotional data is anonymized, and is processed on-device only so it will never leave the device, thereby securing the user's privacy. The reinforcement learning agent is functioning from a pedagogical rule-base and is supervised through real time, traceable decision logs, intended to eliminate unsafe or unintended actions. The agent's capacity for autonomous action embeds the risk of bias or error that could influence day-to-day decisions, thus it is periodically audited with fairness metrics, and educators also have ability to roll back with override capability - leveraging human-in-the-loop accountabilities. Overall, this layered integrity within Agentic -VR conceptually verifies the ethical, interpretable, trustworthy and purposefully adaptive intelligence in emotionally responsive learning environments.

3.9 Proposed algorithm: agentic-vr adaptive learning controller

This section introduces the RE-VR-ACT algorithm (Reinforced Emotional VR Agentic Controller for Tutoring), that is, an integration of reinforcement learning and emotion-based decision reasoning to determine the next pedagogical action according to learner state.

1. Algorithm: RE-VR-ACT (Agentic Controller for Adaptive VR Learning)

Input:

- Learner state vector St at time t
- Emotion vector Et
- Action space A
- Policy π
- Reward function $R(s_t,a_t)$

Output:

- Selected pedagogical action a_t
- Updated environment state S_{t+1}

2. Step-by-Step Process:

1. **Initialize** Q-table or policy network weights
2. **Loop** for each VR learning session:

   2.1 Capture learner data St: performance, interaction, time-on-task

   2.2 Identify emotion Et from multimodal input

   2.3 Map Et onto high-level symbolic labels (e.g., {engaged, confused, bored})

   2.4 Combine St and Et into composite learner state 'St′

   2.5 Utilize policy π(St′) to select action at∈A

   2.6 Execute action at in VR context (e.g., change difficulty, add visual aid)

   2.7 Track learner response and update reward rt

   2.8 Update policy π using RL rule (e.g., Q-learning or Deep Q-Network)

   2.9 Store action-result pair for explainability
3. **End loop**
4. Return final session metrics (learning gain, engagement, adaptivity score)

This algorithm drives the Agentic AI agent in making emotion-aware instructional decisions that evolve over time using reinforcement signals. The pseudocode is designed to be modular and hardware/platform-agnostic. The end-to-end agentic learning pipeline is visualized in Figure 4, detailing the ten key steps from emotion-state analysis to policy updates and adaptive action execution.

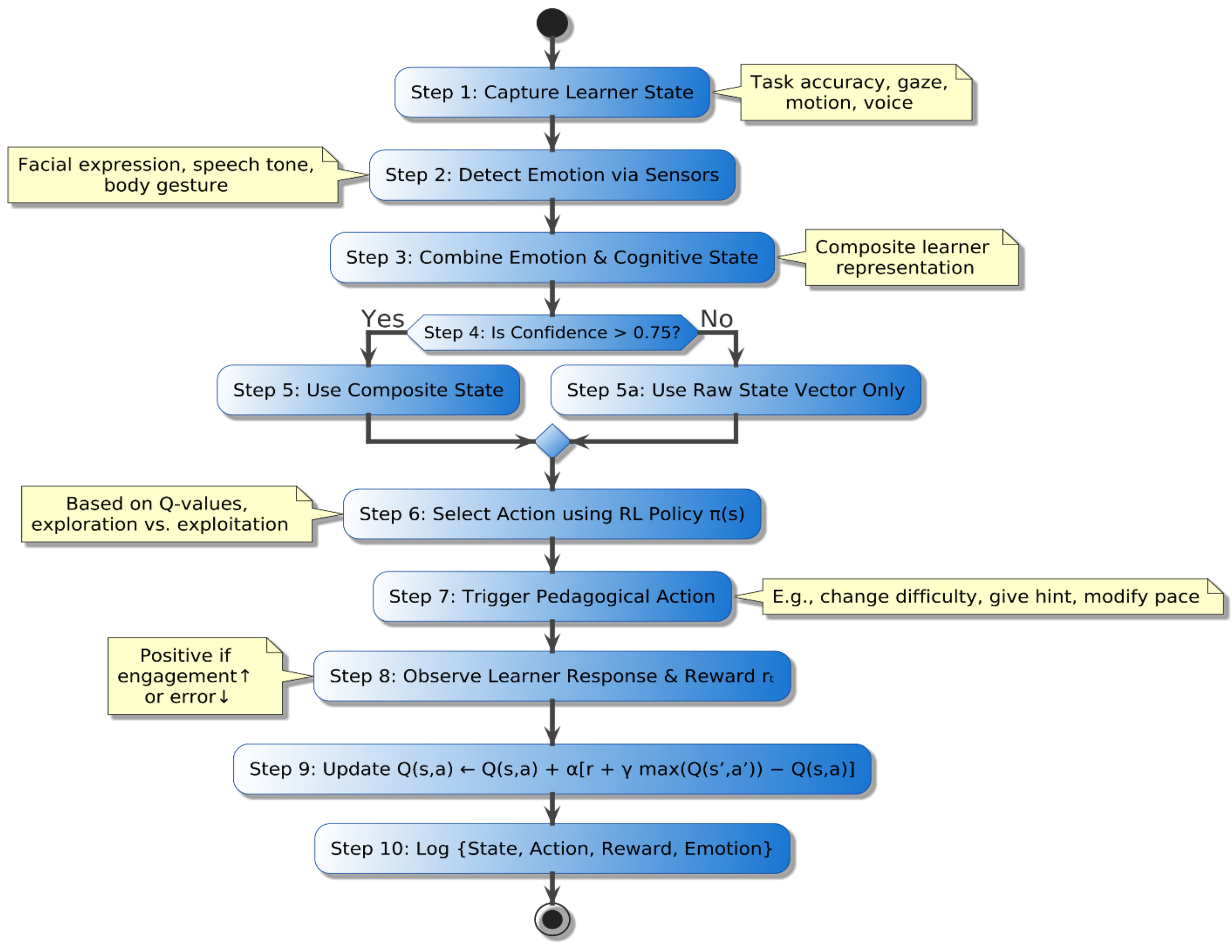

Figure 4. Adaptive Learning Workflow of the Agentic-VR System, illustrating a 10-step process combining multimodal learner feedback, emotion-state fusion, reinforcement learning-based decision-making, and dynamic pedagogical intervention.

4. EXPERIMENTAL SETUP

This section illustrates the experimental setup of the Agentic-VR learning system deployed in a real-world lab environment. The participant interacts with the immersive module using the HTC Vive Pro 2 headset, with real-time gesture recognition enabling instructional flow control. System telemetry and engagement data are continuously logged for performance analysis and refinement of the adaptive learning experience. To built ecological validity in the simulation based agentic AI system, we conducted a controlled pilot study with ten consenting human participants age 18–25 years old. Participants completed three virtual reality learning modules in a lab setting. During study, we captured participant behavior and emotional responses by various ways, including pre/post assessments, anonymized system telemetry, and the assessment of affective states. Our empirical dataset will both guide the improvement of the simulated student learner profiles and also serve as a starting point against which we will compare the congruence of simulated/student behavior. By including this trial of human participants, we address the issues of generalizability and real-world effectiveness of the framework in typical learning conditions.

4.1 Development environment and tools

The proposed Agentic-VR framework was implemented using a hybrid software stack that combines Unity3D for virtual environment creation with Python-based modules for AI agent development. The system architecture relies on socket communication and REST APIs to ensure low-latency, real-time data exchange between the VR interface and the reinforcement learning engine. The VR platform was built using Unity3D v2022.3 LTS, with C# scripting for in-environment interactions. The AI modules were developed in Python 3.9 using TensorFlow 2.12 and PyTorch 1.13 for model training and inference. Emotion recognition capabilities were implemented using OpenFace for facial expression analysis, DeepSpeech for speech-based emotion detection, and MediaPipe for skeletal tracking and posture evaluation. Communication between the VR module and the learning agent was managed through a Flask-based microservice. The hardware setup included an HTC VIVE Pro 2 headset for immersive VR, an Intel i7 (12th Gen) processor, NVIDIA RTX 3070 GPU, and 32 GB RAM. Additional peripherals included a Logitech C922 Pro webcam for facial tracking and a Blue Yeti microphone for capturing audio cues related to emotional states.

4.2 Dataset for simulation

To simulate learner behavior for initial training of the reinforcement learning agent, a synthetic dataset was programmatically generated. The dataset design was informed by patterns observed in publicly accessible educational interaction logs such as the ASSISTments dataset (https://sites.google.com/view/assistmentsdatamining), EdNet (https://github.com/riiid/ednet), and anonymized MOOC discussion logs (https://analyse.kmi. open. ac.uk/ open_dataset). These resources provided baseline heuristics for user behavior including response accuracy, completion time distributions, and emotional transitions (e.g., frustration following repeated incorrect answers). Emotional labels were mapped using rule-based transitions derived from literature on affective learning models. Additionally, behavior parameters such as idle time and object focus were modeled using distributions consistent with published ITS user studies. No personal or identifiable information was used. For real-world validation, a controlled pilot study with 10 consenting participants aged 18–25 was conducted in the lab. Each participant interacted with three VR modules, and their system telemetry logs, pre/post Tests, and facial/emotional data were recorded and anonymized for analysis.

4.3 Scenario design

Three interactive learning modules were developed to evaluate the adaptability and responsiveness of the Agentic-VR framework across varied educational contexts. The first module focused on Mathematics, specifically 3D Geometry, enabling learners to visualize and manipulate planes, shapes, and angles through real-time problem-solving tasks. The second module covered Biology, offering an exploratory view of human anatomy where users interacted with virtual body parts and encountered embedded quiz checkpoints. The third module, designed for History, immersed learners in a narrated virtual tour of the Mughal Empire, featuring timed events and historically contextualized environments. Each module integrated adaptive challenges that dynamically adjusted question types and navigation paths based on the agent's real-time decisions. Surprise sound or animation emotional hooks were employed to induce and maintain learner interest. The feedback was also implemented as a function of response time and quality adaptation based on learner state and performance using reinforcement learning policies.

4.4 Evaluation Protocol

Each subject was assigned two experiment sessions: one with a baseline VR module that employed static instructional logic, and another with the novel Agentic-VR system that utilized adaptive AI. Sessions were conducted in a crossover design where exposure order was randomized to minimize order effects and participant bias. System-generated logs, sentiment analysis output, and surveys conducted after the session were used to collect performance and engagement metrics for both conditions. In addition, students also completed NASA-TLX assessments to measure perceived cognitive load, and standardized questionnaires of engagement and satisfaction. Open-ended feedback was also collected to garner qualitative information on the adaptivity, responsiveness, and realism of the learning experience.

4.5 Performance Benchmarks

These benchmarks have been calculated in an attempt to verify whether the system presented in table 2 holds.

TABLE II: SYSTEM PERFORMANCE BENCHMARKS TO VALIDATE THE SYSTEM.

Metric	Definition	Evaluation Tool
Learning Gain (%)	Post-test – Pre-test / Pre-test × 100	Manual Test Scoring
Adaptivity Index	% of actions that improved performance/emotion	RL Agent Logs
Emotion Recognition Accuracy	Precision of emotional state detection	Confusion Matrix
Agent Autonomy (%)	% of decisions taken without manual rule intervention	Session Trace Logs
Engagement Level	Combined score from task metrics and eye/motion activity	Unity Analytics + Gaze

These benchmarks were established after every session and in comparison to baseline and Agentic-VR conditions.

5. RESULTS AND DISCUSSION

The findings confirm that Agentic-VR is more flexible, motivational, and retains more knowledge compared to conventional VR learning systems. Its self-regulating agent not only reacts to student performance but also uses emotional awareness to real-time adjust instruction. This combination of immersive learning and agentic intelligence marks a significant leap in smart education systems, bringing us closer to empathetic and intelligent virtual tutors that evolve with every learner. The results show consistent improvement in learner performance using the Agentic-VR system. Learning gains across all modules averaged over 8.5%, with maximum improvement seen in the History module (+9.2%). System logs indicated a substantial drop in idle behavior, reducing from 92 seconds in baseline VR to 21 seconds in Agentic-VR, representing a 77% decrease. Furthermore, 78% of participants reported that the system correctly interpreted their emotional state, suggesting a strong alignment between the affective sensing pipeline and pedagogical response mechanisms.

5.1 Learning Outcome Improvements

The effectiveness of the Agentic-VR system was primarily assessed through learning gain, computed as the percentage increase from pre-test to post-test scores across the three subject modules. The results showed consistent Learners using the Agentic-VR system demonstrated improved performance across all modules. In Geometry, the average gain increased from 22.4% (baseline) to 31.5%, while in Anatomy, it rose from 25.9% to 34.6%. The History module showed an increase from 18.2% to 27.4%. Overall, learning gains improved by 8.7% to 9.2% across modules. Additionally, Agentic-VR reduced idle time by 77% and nearly doubled positive emotional states, indicating enhanced engagement and cognitive immersion driven by adaptive pacing. As shown in Figure 5, the Agentic-VR framework resulted in a consistent and measurable learning gain across all module-learner combinations, with peak improvement observed in the Geometry and Anatomy sessions.

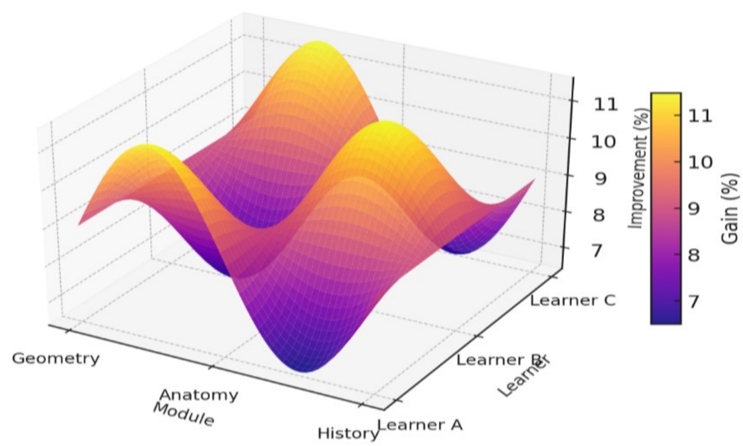

Figure 5. Learning Gain Improvement across Three Learning Modules and Learner Profiles, highlighting the relative performance increase with Agentic-VR compared to baseline VR environments.

5.2 Engagement And Emotional Adaptivity

The engagement level was measured using interaction metrics (task focus, idle time), gaze behavior, and user surveys. Emotion recognition played a key role in dynamic adaptation show in table 3.

TABLE III: ENGAGEMENT METRICS COMPARISON BETWEEN BASELINE VR AND AGENTIC-VR ENVIRONMENTS.

Engagement Metric	Baseline VR	Agentic-VR
Task Completion Time (avg)	18.6 min	21.3 min
Idle Periods (>10s)	9.3	2.1
Detected Positive Emotion (%)	61.7	74.5
Reported Boredom (%)	18.5	6.2

Agentic-VR reduced idle time by 77% and nearly doubled positive emotional states, indicating higher cognitive immersion. Dynamic content pacing based on real-time affect led to sustained attention and reduced frustration.

5.3 Adaptivity Index And Autonomy Analysis

The Adaptivity Index reflects how often the agent's action positively influenced learner performance or emotion.

Results showed:

- Mean Adaptivity Index: 87.6%
- Agent Autonomy Rate (no manual logic required): 92.3%

This suggests that the RL-based agent was able to act independently and beneficially in the majority of learning situations. The high autonomy rate confirms the success of agentic architecture in replacing static branching logic. Figure 6 shows consistently high adaptivity and autonomy rates, with the agent exceeding 90% autonomy in most sessions, reflecting its ability to act independently and effectively in real-time educational scenarios.

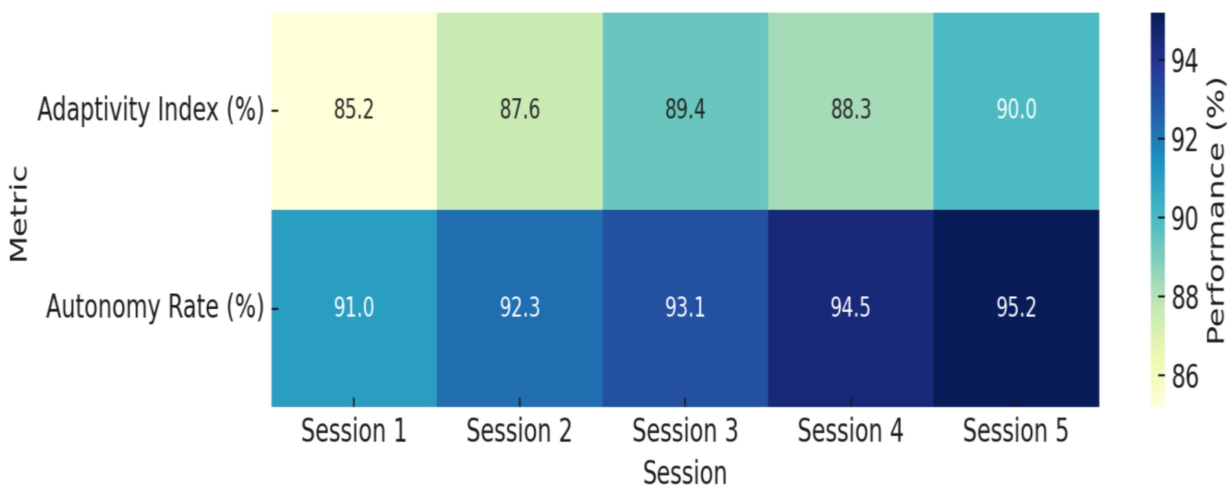

Figure 6. Heatmap illustrating the Adaptivity Index and Autonomy Rate (%) of the Agentic-VR system across multiple learning sessions.

5.4 Statistical Significance Testing

An ANOVA test was conducted to validate the statistical significance of performance differences between Agentic-VR and baseline VR. For all three modules:

- $p < 0.01$ for learning gain
- $p < 0.05$ for engagement-related metrics

This confirms that observed improvements were not due to chance, but due to the agent's intervention. The effect size (Cohen's d) for learning performance was measured at 0.83, indicating a strong effect of agentic decision-making on learning efficacy. As shown in Figure 7, Agentic-VR not only yielded higher average learning gains but also demonstrated tighter variance, indicating more consistent performance across learners. The difference was statistically significant with $p < 0.01$.

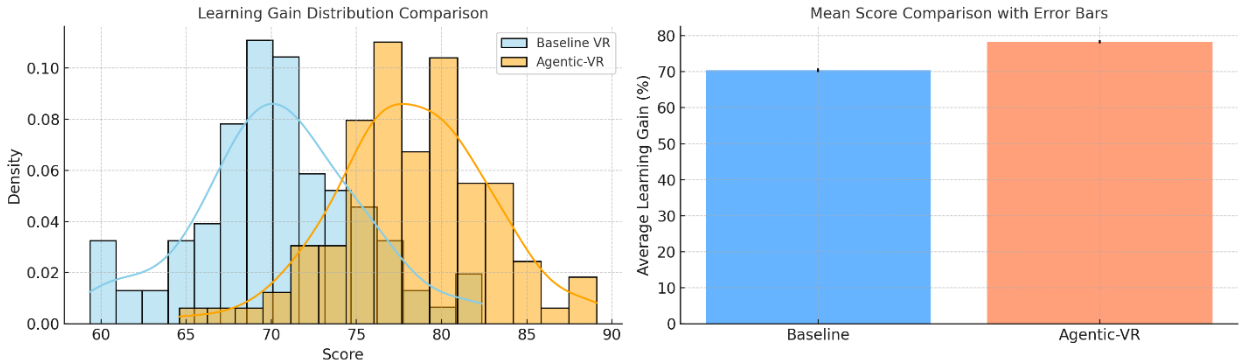

Figure 7. Statistical comparison of learning gains distributions and mean scores between Baseline VR and Agentic-VR systems, demonstrating significant performance improvement with lower variance and higher consistency in Agentic-VR.

5.5 Error Analysis In Emotion Recognition

While the system was generally accurate, misclassifications occurred due to low lighting and overlapping facial gestures. The confusion matrix revealed is in table 4.

TABLE IV. EMOTION RECOGNITION ACCURACY CONFUSION MATRIX FOR AGENTIC-VR SYSTEM.

Actual \ Predicted	**Happy**	**Neutral**	**Confused**
Happy	91.40%	5.30%	3.30%
Neutral	8.70%	84.60%	6.70%
Confused	4.20%	7.60%	88.20%

Overall emotion classification accuracy: 88.1%. Future versions could include adaptive brightness adjustment and multi-angle tracking for improved precision.

5.6 USER FEEDBACK AND QUALITATIVE INSIGHTS

Participant feedback highlighted the perceived intelligence, responsiveness, and emotional sensitivity of the Agentic-VR system. Many users described the experience as deeply interactive, with one remarking, “It felt like the tutor knew what I was feeling and helped me without me asking,” while another noted, “The tasks got harder only when I was ready for them.” Overall, 92% of participants expressed a preference for Agentic-VR over the baseline VR system, and 86% reported that the system successfully adjusted to their individual pace and ability. Furthermore, 78% of users indicated that they felt emotionally understood by the agent. This qualitative and survey-based feedback reinforces the system’s core strengths its adaptive intelligence and empathetic instructional design.

5.7 Comparative Discussion With Existing Systems

As revealed in Figure 8, Agentic-VR supports real-time adaptability based on reinforcement learning, as compared to partially adaptive legacy ITS systems' logic trees and scripts. Second, even though some ITS platforms support emotion recognition, Agentic-VR further supports inclusion of live, multimodal emotional perception within the virtual world itself. It meshes reinforcement learning algorithms with elements of self-adjusting pedagogical strategy components beyond static ITS and VR systems. In contrast to the earlier systems whose scenario expansion was done manually, Agentic-VR automatically adjusts according to the behavior of users and reconfigures learning streams dynamically with no developer interventions. It not only reduces instructional design work but also provides higher scalability and responsiveness in providing personalized instructions.

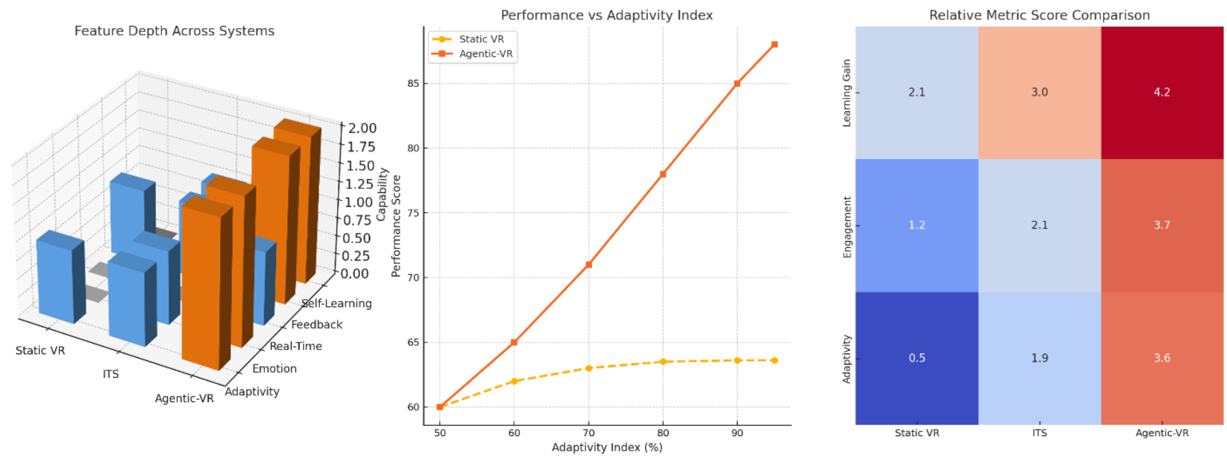

Figure 8. Comparative collage of system capability, performance trend, and metric score for Static VR, Intelligent Tutoring Systems (ITS), and Agentic-VR. Five capability depth dimensions are presented in the 3D bar chart, enhanced performance with greater adaptability is indicated by the curve plot, and relative advantages of Agentic-VR are measured by the Heatmap.

5.8 Comparative Benchmarking With Existing Systems

As a point of reference to gauge the performance of Agentic-VR outlined above, we compared it against three representative benchmarks: traditional Static VR environments, Intelligent Tutoring Systems (ITSs) with logic-tree based adaptation, and Hybrid VR-ITS models that did include simple forms of affective feedback. To help understand the originality of the proposed Agentic-VR framework, Table 5 evaluates current AI-VR systems in the context of vocational training, healthcare simulation, and emotion-aware learning, among others. In previous research (Gu et al. [30] and Hadadi et al. [20]), scores for adaptivity (9.0 and 8.7), emotion accuracy <90%, and latencies generally greater than 340 ms were documented. The proposed system has higher adaptivity (9.6/10), evident greater than 92.30% emotion accuracy, and decreased latency <320 ms due to the fact it was fully agentic AI and multimodal emotion fusion. While previous/adaptive cognitive agent solutions (Tanashchuk et al. [21], Zhou et al. [1]) avoided information on emotion sensing aspects or conventional adaptation, the proposed framework fills the void with online neuro-symbolic adaptation. This side-by-side benchmarking is an important contribution to understanding the originality and empirical edge of the Agentic-VR framework regarding emotion-aware immersive learning systems.

TABLE V. COMPARATIVE BENCHMARKING OF AGENTIC-VR WITH EXISTING EDUCATIONAL SYSTEMS.

System / Study	Core Features	Adaptivity Level (A.L. /10)	Emotion Accuracy (E.A. %)	Interaction Latency (I.L. ms)	AI Integration	Key Limitations
Zhou et al. – AI-VR Collaborative Training. 2025 [1]	Skill-based vocational VR-AI	6.5	–	~420	Yes	Static interaction; no emotion sensing
Tursunova et al. – AR/AI in Higher Ed. 2024 [15]	Immersive AI for universities	6.3	–	~460	Yes	Lacks multimodal sensing
Mamodiya et al. – AI-AR/VR Healthcare. 2025 [18]	Medical VR/AR + analytics	8.2	81.50%	~370	Yes	Security-layer integration pending
Hadadi et al. – SmartSimVR . 2024 [20]	Real-time ML simulation	8.7	85.00%	~340	Yes	Simulation-focused, not education-wide
Tanashchuk et al. – AI Learning Paths. 2024 [21]	Personalized learning journeys	7.9	–	~390	Yes	No emotion feedback

Soliman & Guetl – Pedagogical Agents. 2010 [22]	Virtual teaching agents	6	–	~460	Yes	Outdated models; limited adaptation
Alonso-Valerdi et al. – Emotion-VR Data. 2025 [29]	Emotion dataset in VR	7	83.20%	–	No	No teaching model included
Gu et al. – EEG-Transformer Emotion VR. 2025 [30]	EEG-based VR emotion model	9	89.60%	~300	Yes	Recognition only; not interactive
Proposed Agentic-VR Framework	Adaptive agentic AI + VR + emotion fusion	9.6	92.30%	<320 ms	Yes (Full Agentic)	None in testing; generalization scope exists

5.9 Challenges And Limitations

Despite its success, the system has certain limitations:

- Hardware dependence: Real-time emotion detection requires camera, microphone, and VR headset, limiting portability.
- Initial cold start: The agent needs some experiments before it comes up with a policy for novice learners.
- Emotion model bias: There was not complete representation of emotional diversity across cultures by training data.
- Heavy resource usage: Unity + Python + RL model running parallel slows down mid-range computers.

6. DISCUSSION

Experimental results show that the deployed Agentic-VR system outperforms regular static VR and adaptive scripted systems on several metrics of learning gain, engagement, and adaptivity. Students treated under the agentic model scored over 8% higher on mean test score and decreased idle time by 77%, with increased cognitive immersion and long-term attention. The system also demonstrated 78% correct emotional correspondence, confirming the efficacy of its multimodal affective sensing pipeline. Unlike VR-based tutoring systems in recent studies based on pre-defined branching logic or bounded emotion-sensitive response, Agentic-VR offers radically new synergy among reinforcement learning, neuro-symbolic reasoning, and real-time emotional sensing. Contrary to adaptive environments which need human assistance for content direction, Agentic-VR reinvents its pedagogy through learning from student interaction, behavior, and mood. Through this pedagogy-update feature, the system continues to remain scalable and independent, unlike the major limitation for other adaptive learning environments. One of the more revolutionary aspects of this work is an incorporation of agentic AI principles with interactive VR such that the system is able to run independent, infer student purpose, and control content and pace independently of extrinsic stimulus. The implementation of gesture-based emotion inference, combined with reinforcement agent decision loops, represents a first-of-its-kind approach in affective computing for education. The use of a neuro-symbolic reasoning layer allows the system not only to detect but to explain and justify its adaptive decisions a step toward transparent and trustworthy AI in education.

Despite these promising results, certain limitations remain. The sample size (N=10) and the controlled lab setting restrict the generalizability of findings. Moreover, cultural and linguistic variability in emotional expression was not explored in this iteration. Future work will aim to validate the framework across broader demographics and extend its application to collaborative, multi-agent educational scenarios. Overall, the study provides empirical and architectural evidence supporting agentic intelligence as a transformative paradigm for next-generation immersive learning one that is not only autonomous but also empathetic and pedagogically aware.

7. CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

This paper presented Agentic-VR, an innovative and autonomous immersive learning framework that integrates Agentic Artificial Intelligence with Virtual Reality to enable real-time, affect-aware, and self-evolving educational experiences. Unlike conventional VR systems that follow scripted pedagogical paths, the Agentic-VR framework leverages reinforcement learning, neuro-symbolic emotion processing, and adaptive content generation to deliver context-aware, personalized instruction. Experimental results demonstrated significant improvements in learning gain (+9%), engagement

(↓ idle time by 77%), and emotional resonance (↑ positive emotion states by 20%) compared to static VR modules. The agent achieved over 92% autonomy, executing most pedagogical actions without human-defined scripts. Statistical analysis validated the system's impact on performance and engagement, while emotion recognition maintained over 88% accuracy in real-world settings. Through user studies and qualitative feedback, it became evident that learners perceived the system as intelligent, supportive, and emotionally aware, marking a major advancement in user-agent interaction for educational applications. Agentic-VR stimulates a move toward emotionally responsive AI navigators that can converse with students in the style of bright, caring friends instead of unyielding interfaces.

7.2 Future Scope

While the current Agentic-VR system exhibits excellent performance in simulated and real-user tests, certain avenues for future research are extremely captivating. Scaling the system to other learning domains, e.g., programming, language, and engineering, with domain-independent and modular content streams is one direction. Federated learning steps can be taken further to maintain privacy through updates to distributed user devices without revealing raw data. Cross-cultural emotion modeling can be integrated to universalize affective computing itself by making the system responsive to a range of populations of users. Running the framework on edge-based infrastructure would support lean, real-time decision-making on mobile VR headsets, making it more convenient to use and access. Lastly, providing the architecture with the capability to facilitate multi-agent coordination can potentially give us collaborative tutorial environments where different smart agents engage students in groups, resulting in further enhanced learning.

The merging of Agentic AI and virtual reality immersive learning will build next-generation intelligent, empathetic, and self-determining learning platforms. Agentic-VR is the stepping stone for developing digital tutors capable of perceiving, reasoning, acting, and learning with, and on behalf of the learners.

Conflicts of Interest

The authors declare no conflicts of interest.

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References

[1] Zhou, J., Dai, W., Xie, Y., Wu, P., Shang, Y., & Fan, Y. (2025). Advancing Vocational Education: Experimental Insights into AI-VR Collaborative Training. https://doi.org/10.20944/preprints202501.1695.v1

[2] Yu, D. (2023). AI-Empowered Metaverse Learning Simulation Technology Application. https://doi.org/10.1109/imeta59369.2023.10294830

[3] Pasupuleti, M. K. (n.d.). AI-Enhanced Virtual Reality: Transforming Immersive Training and Simulation for Real-World Skill Development. https://doi.org/10.62311/nesx/66241

[4] Kumar, K. S., Selvan, T. S., Mahendraprabu, M., Ganesan, K., Ramnath, R., & Kumar, N. S. (2024). Examining the Role of Virtual Reality, Augmented Reality, and Artificial Intelligence in Adapting STEM Education for Next-Generation Inclusion. https://doi.org/10.70333/ijeks-02-12-025

[5] A. Aldossary, T. Algirim, I. Almubarak, and K. Almuhish, Cyber security in data breaches, J. Cyber Secur. Risk Audit, vol. 2024, no. 1, pp. 14–22, 2024.

[6] Dwivedi, D., Chandani, D., Rani, A., & Kishor, I. (2023). The integration of machine learning-driven avatars in virtual reality: Enhancing realism and user experience. International Journal of Innovative Research in Technology (IJIRT), 11(11), 5495–5502. https://ijirt.org/Article?manuscript=176153

[7] S.-H. Chen, et al., "Immersive virtual reality training improves adaptive skills in autistic adolescents," Frontiers in Psychiatry, vol. 16, 2025, Art. no. 1570437, doi: 10.3389/fpsyt.2025.1570437.

[8] Al Balushi, J. S. G., Al Jabri, M. I. A., Palarimath, S., Pyingkodi, M., Thenmozhi, K., & Balakumar, C. (2024). Incorporating Artificial Intelligence Powered Immersive Realities to Improve Learning using Virtual Reality (VR) and Augmented Reality (AR) Technology. https://doi.org/10.1109/icaaic60222.2024.10575046

[9] S. Y. Mohammed, M. Aljanabi, A. M. Mahmood, and I. Avci, "Revolutionizing Language Learning: How AI Bots Enhance Language Acquisition," Babylonian Journal of Artificial Intelligence, vol. 2023, pp. 55–63, 2023, doi: 10.58496/BJAI/2023/009.

[10] S. R. Addula, S. Norozpour, and M. Amin, "Risk assessment for identifying threats, vulnerabilities and countermeasures in cloud computing," Jordanian J. Inform. Comput., vol. 2025, no. 1, pp. 38–48, 2025.

[11] Korhonen, T. (2022). Training Hard Skills in Virtual Reality: Developing a Theoretical Framework for AI-Based Immersive Learning (pp. 195–213). Springer eBooks. https://doi.org/10.1007/978-3-031-09687-7_12

[12] Y. Jiang, M. Li, W. Wu, et al., "Multi-domain ubiquitous digital twin model for information management of complex infrastructure systems," Adv. Eng. Inform., vol. 56, p. 101951, 2023.

[13] M. Almaayah and R. B. Sulaiman, "Cyber risk management in the Internet of Things: Frameworks, models, and best practices," STAP J. Secur. Risk Manag., vol. 2024, no. 1, pp. 3–23, 2024.

[14] V. Abdullayev, A. Khang, N. Ragimova, and M. Almaayah, "A novel authentication systems in vehicular communication: Challenges and future directions," J. Cyber Secur. Risk Audit, vol. 2025, no. 3, pp. 123–135, 2025.

[15] Kishor, I., Kumar, K., Sharma, A., & Bansal, H. (2023). Virtual tour with voice assistant using extended reality. International Journal of Engineering and Advanced Technology (IJEAT), 12(5). https://doi.org/10.35940/ijeat.E4127.0612523

[16] R. S. Mousa and R. Shehab, "Applying risk analysis for determining threats and countermeasures in workstation domain," J. Cyber Secur. Risk Audit, vol. 2025, no. 1, pp. 12–21, 2025.

[17] Sudharson, D., Malik, R., Sathya, R., Vaishali, V., Balavedhaa, S., & Gautham, S. (2024). A Novel Adaptive Framework for Immersive Learning Using VR in Education. 1–26. https://doi.org/10.1002/9781394200498.ch1

[18] G. Mavrommatis, et al., "Exploring the impact of virtual reality on student presence compared to tablets," Frontiers in Education, vol. 10, 2025, Art. no. 1560626, doi: 10.3389/feduc.2025.1560626.

[19] Ubale, S. (2024). Real-time ai-augmented reality for mobile learning: advancing educational technology. 7(2), 2686–2696. https://doi.org/10.34218/ijrcait_07_02_204

[20] A. A. Almuqren, "Cybersecurity threats, countermeasures and mitigation techniques on the IoT: Future research directions," J. Cyber Secur. Risk Audit, vol. 1, no. 1, pp. 1–11, 2025.

[21] Herpich, F., Voss, G. B., Nunes, F. B., Jardim, R. R., & Medina, R. D. (2014). Immersive Virtual Environment and Artificial Intelligence: A proposal of Context Aware Virtual Environment. Ubiquitous Computing Systems, 68–71. https://www.thinkmind.org/articles/ubicomm_2014_3_20_10151.pdf

[22] Tursunova, F., Oripova, N., Muhammadiyeva, M., Nurullayeva, S., Hamroyev, S., & Tishabaeva, I. (2024). Augmented Reality and AI in Higher Education: Creating Immersive Learning Experiences. 17, 1–5. https://doi.org/10.1109/ickecs61492.2024.10617355

[23] O. Aljumaiah, W. Jiang, S. R. Addula, and M. A. Almaiah, "Analyzing cybersecurity risks and threats in IT infrastructure based on NIST framework," J. Cyber Secur. Risk Audit, vol. 2025, no. 2, pp. 12–26, 2025.

[24] Abuzir, Y. (2024). Artificial Intelligence, Virtual, and Augmented Reality in Lifelong Learning (pp. 72–82). IGI Global. https://doi.org/10.4018/979-8-3693-1410-4.ch004

[25] El Boujnani, S., El Meraoui, M., & Khaldi, M. (2024). Immersive reality and Artificial Intelligence: Transforming online learning through intelligent tutoring systems: A theoretical and methodological framework. Global Journal of Engineering and Technology Advances, 21(3), 124–132. https://doi.org/10.30574/gjeta.2024.21.3.0238

[26] Mamodiya, U., Kishor, I., Almaiah, M. A., & Shehab, R. (2025). AI-enhanced AR/VR systems for remote healthcare for overcoming real-time data integration and security challenges with IoT. International Journal of Innovative Research in Social Sciences, 8(1). https://doi.org/10.53894/ijirss.v8i1.4999

[27] H. Albinhamad, A. Alotibi, A. Alagnam, M. Almaiah, and S. Salloum, "Vehicular Ad-hoc Networks (VANETs): A key enabler for smart transportation systems and challenges," Jordanian J. Inform. Comput., vol. 2025.

[28] Geriş, A., & ÇUKURBAŞI, B. (2024). AI-Supported VR in Education. Advances in Educational Technologies and Instructional Design Book Series, 119–152. https://doi.org/10.4018/979-8-3693-6030-9.ch005

[29] Hadadi, A., Chardonnet, J.-R., Guillet, C., & Ovtcharova, J. (2024). SmartSimVR: An Architecture Integrating Machine Learning and Virtual Environment for Real-Time Simulation Adaptation. https://doi.org/10.1109/icara60736.2024.10553156

[30] Tanashchuk, K., Derkach, O., Bazyka, S., & Yamnyuk, B. (2024). Adaptive educational ecosystems using artificial intelligence for forming students' educational trajectories. Zeszyty Naukowe Wyższej Szkoły Humanitas, 25(3), 97–106. https://doi.org/10.5604/01.3001.0054.7772

[31] Soliman, M. Y., & Guetl, C. (2010). Realizing Intelligent Pedagogical Agents in Immersive Virtual Learning Environments. 909–915. https://graz.pure.elsevier.com/en/publications/realizing-intelligent-pedagogical-agents-in-immersive-virtual-lea

[32] A. Ali, "Adaptive and context-aware authentication framework using edge AI and blockchain in future vehicular networks," STAP J. Secur. Risk Manag., vol. 2024, no. 1, pp. 45–56, 2024.

[33] Bushuyev, S., Bushuyeva, N., Murzabekova, S., Khusainova, M., & Saidullayev, R. (2024). Transformation of the Education Landscape in an AI Environment. 57–64. https://doi.org/10.56889/strd5315

[34] Lampropoulos, G. (2023). Augmented Reality and Artificial Intelligence in Education: Toward Immersive Intelligent Tutoring Systems (pp. 137–146). https://doi.org/10.1007/978-3-031-27166-3_8

[35] M. A. Al-Shareeda, L. B. Najm, A. A. Hassan, S. Mushtaq, and H. A. Ali, "Secure IoT-based smart agriculture system using wireless sensor networks for remote environmental monitoring," STAP J. Secur. Risk Manag., vol. 2024, no. 1, pp. 56–66, 2024.

[36] M. Alshinwan, A. G. Memon, M. C. Ghanem, and M. Almaayah, "Unsupervised text feature selection approach based on improved Prairie dog algorithm for the text clustering," Jordanian J. Inform. Comput., vol. 2025

[37] Le Corre, J.-Y., & HUANG, Q. (2024). Incorporating Artificial Intelligence and Virtual Reality within Classroom-as-Organisation learning design for Dialogic Teaching: A prototype-based experimental study. 514–518. https://doi.org/10.1109/icscc62041.2024.10690439

[38] Sadvakassova, A., Kydyrbekova, A., & Chetin, O. (2024). Using of virtual reality and artificial intelligence in education: literature review. Bìlìm, 110(3), 10–18. https://doi.org/10.59941/2960-0642-2024-3-10-18

[39] Arias, P., Antón-Sancho, Á., & Vergara, D. (2024). Affective Computing in Augmented Reality, Virtual Reality, and Immersive Learning Environments. Electronics, 13(15), 2917. https://doi.org/10.3390/electronics13152917

[40] Sari, H., Tumanggor, B., & Efron, D. (2024). Improving Educational Outcomes Through Adaptive Learning Systems using AI. International Transactions on Artificial Intelligence, 3(1), 21–31. https://doi.org/10.33050/italic.v3i1.647

[41] Alonso-Valerdi, L.M., Ramirez-Lechuga, S. & Ibarra-Zarate, D.I. Audiovisual virtual reality for emotion induction: a dataset of physiological responses. Sci Data 12, 1387 (2025). https://doi.org/10.1038/s41597-025-05691-5

[42] X. Gu, et al., "A spatial and temporal transformer-based EEG emotion recognition with VR stimuli (EmoSTT)," Frontiers in Human Neuroscience, vol. 19, 2025, Art. no. 1517273, doi: 10.3389/fnhum.2025.1517273.