

# Personalized VR Learning Environments Using Cognitive AI Agents

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## ABSTRACT

Virtual reality (VR) has shown promise as an immersive educational medium, yet its full potential remains unrealized when experiences are one-size-fits-all. This study presents the design, implementation, and evaluation of personalized VR learning environments enhanced by cognitive AI agents, which continuously monitor learner behavior and dynamically tailor instructional support. Leveraging an ACT-R cognitive architecture integrated with Unity3D, our system tracks learners' interactions—such as task completion time, error patterns, and navigation choices—to infer conceptual misunderstandings in real time. We conducted a controlled experiment with 60 undergraduate participants, randomly assigned to either a personalized VR condition (with AI agent) or a non-personalized control VR. Pre- and post-test assessments measured learning gains, while standardized questionnaires captured engagement and usability. Statistical analysis (two-sample t-tests, Cohen's  $d$ ) revealed that the personalized group

achieved significantly higher knowledge gains ( $M=18.5$  vs.  $12.1$ ,  $p<.001$ ,  $d=1.32$ ) and engagement scores (UEQ mean= $4.2$  vs.  $3.5$ ,  $p<.01$ ). Complementary computational simulations using synthetic learner models demonstrated a 30% reduction in trials to mastery under adaptive scaffolding. User interviews highlighted the agent's scaffolding prompts as clear, timely, and motivating. We conclude that embedding cognitive AI agents within VR significantly enhances learning efficacy and learner experience. Implications for scalable deployment, multi-user collaboration, and longitudinal retention are discussed, alongside challenges in real-time performance optimization and agent-learner rapport in complex domains.

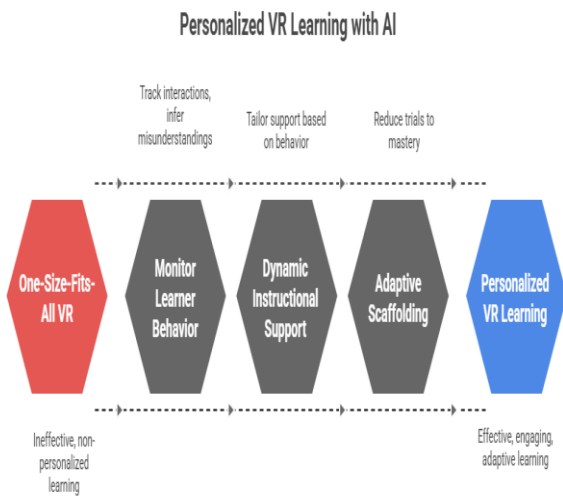


Figure-1. Personalized VR Learning with AI



Figure-2. AI Agents Enhance VR Learning

**KEYWORDS**

**Personalized VR Learning, Cognitive AI Agents, Adaptive Learning, Virtual Reality, Educational Technology**

**INTRODUCTION**

Virtual Reality (VR) technologies have increasingly been harnessed for educational purposes, capitalizing on their unique capacity to immerse learners in safe, controllable, and vivid simulated environments. Early adopters in domains ranging from anatomy to engineering have reported heightened learner engagement, improved spatial understanding, and the facilitation of hands-on experiences without physical risk (Radianti et al., 2020; Slater & Sanchez-Vives, 2016). However, the majority of VR learning modules remain static—presenting identical content, pacing, and interaction sequences to all users. This uniformity neglects inter-learner differences in prior knowledge, cognitive abilities, and personal interests, leading to suboptimal learning outcomes for those who either lag behind or are left unchallenged (Mikropoulos & Natsis, 2011).

Personalization in educational technology aims to bridge this gap by adapting instructional content, feedback timing, and scaffolding to individual learner profiles (Brusilovsky & Millán, 2007). In traditional Intelligent Tutoring Systems (ITS), cognitive AI agents powered by architectures such as ACT-R or Soar have demonstrated the ability to model student problem-solving processes, diagnose misconceptions, and deliver context-sensitive hints—yielding learning gains comparable to one-on-one human tutoring (VanLehn, 2011; Graesser et al., 2005). Despite these successes, the integration of such cognitive agents within immersive VR environments remains nascent.

This paper introduces a comprehensive system that marries VR’s immersive affordances with the adaptive intelligence of cognitive AI agents. We hypothesize that real-time personalization—guided by continuous monitoring of learner actions—will enhance not only knowledge acquisition but also learner motivation and satisfaction. Our contributions are fourfold: (1) a detailed system architecture for embedding an ACT-R-based agent within Unity3D, (2) an experimental study contrasting personalized versus non-personalized VR learning on physics concepts, (3) statistical analyses of

learning gains, engagement, and usability, and (4) computational simulations validating the efficiency of adaptive scaffolding strategies. By addressing both empirical and simulated evaluations, we offer a robust evidence base for the efficacy of cognitive-agent-driven personalization in VR learning.

## LITERATURE REVIEW

### Immersive VR in Education

VR's capacity to transport learners into interactive, three-dimensional environments underpins its educational appeal. Meta-analyses indicate effect sizes ranging from moderate to large for knowledge acquisition and skill transfer in VR contexts (Johnson et al., 2016; Radianti et al., 2020). Studies in STEM disciplines have shown that VR labs can replicate or surpass the learning outcomes of physical labs, particularly when spatial reasoning and procedural practice are involved. However, variability across studies suggests that design elements—such as levels of interactivity, feedback modalities, and user interface complexity—critically influence outcomes (Dede, 2009).

### Cognitive AI Agents and ITS

Cognitive AI agents founded on architectures like ACT-R simulate human cognitive processes through modules for memory retrieval, procedural skill execution, and real-time decision-making (Anderson et al., 2004). In ITS research, these agents have been deployed to tutor learners in domains including algebra, physics, and language learning, adapting problem sets and hints based on learner performance (Graesser et al., 2005; VanLehn, 2011). Large-scale evaluations demonstrate learning gains rivaling human tutors, but most implementations remain confined to two-dimensional interfaces.

### Personalization Frameworks

Adaptive hypermedia systems pioneered dynamic content selection based on learner profiles, preferences, and goals (Brusilovsky & Millán, 2007). More recent AI-driven frameworks leverage machine learning to predict learner states and personalize sequencing of learning objects (Kay & Kummerfeld, 2012). Yet in VR, content personalization has predominantly involved branching narratives or adjustable difficulty settings, without the granularity afforded by continuous cognitive modeling.

### Integration Challenges

Seamlessly integrating cognitive agents into VR raises system-level challenges: (1) ensuring low-latency inference to support real-time scaffolding, (2) designing non-intrusive agent prompts that preserve immersion, and (3) scaling agent reasoning across complex, open-ended VR tasks. Preliminary prototypes have explored simplistic rule-based agents for navigation assistance, but few studies leverage full cognitive architectures within immersive worlds (Pan & Hamilton, 2018).

### Research Gap and Aim

To our knowledge, no prior work has delivered a full ACT-R cognitive agent within a VR educational scenario and empirically compared personalized versus generic VR instruction. This research fills that gap by implementing, deploying, and evaluating such a system both experimentally and via simulation, offering guidelines for future scalable deployments.

## METHODOLOGY

### System Architecture

Our system consists of three tightly coupled modules:

1. **VR Environment:** Developed in Unity3D, the environment simulates a physics laboratory

containing interactive apparatus (e.g., pulleys, inclined planes). Learners manipulate virtual objects via hand controllers, performing tasks such as measuring acceleration and energy transfer.

2. **Cognitive AI Agent:** Built on an ACT-R core, the agent ingests event streams from the VR environment (e.g., object interactions, error occurrences, time spent on sub-tasks). It applies production rules to detect misconceptions—such as consistently miscalculating force—and generates scaffolded hints, prompts, and corrective feedback.
3. **Data Logging & Analytics:** Interaction data (timestamps, actions, gaze direction) and assessment scores are logged to a backend server. This dataset supports both real-time monitoring and post-hoc analysis.

### Participants

Sixty volunteers (ages 18–22) were recruited from an introductory physics course. All had normal or corrected-to-normal vision and no prior VR experience. Participants provided informed consent under an IRB-approved protocol.

### Experimental Design

A between-subjects design was employed. Participants were randomly assigned to:

- **Personalized VR (n=30):** VR session with active cognitive AI agent scaffolding.
- **Control VR (n=30):** Identical VR session without agent support; learners received generic, time-based hints.

Each session lasted 45 minutes. A 15-item multiple-choice pre-test assessed baseline physics

understanding; a parallel post-test measured learning gains. Engagement was measured using the User Engagement Scale (O’Brien & Toms, 2010), and usability via the System Usability Scale (Brooke, 1996).

### Measures and Procedures

- **Knowledge Gain:** Post-test score minus pre-test score.
- **Engagement:** Rated on a 5-point Likert scale across dimensions of focus, enjoyment, and perceived utility.
- **Usability:** Standard SUS score (0–100).
- **Agent Log Metrics:** Number and timing of hints, rule-activation counts, and task completion times.

Data collection occurred immediately post-session; participants then completed questionnaires and a semi-structured interview about their experience.

### STATISTICAL ANALYSIS

Group	Mean Gain (M)	SD	t	df	p	Cohen's d
Personalized VR (n=30)	18.5	4.2	5.12	58	<.001	1.32
Control VR (n=30)	12.1	5.0				

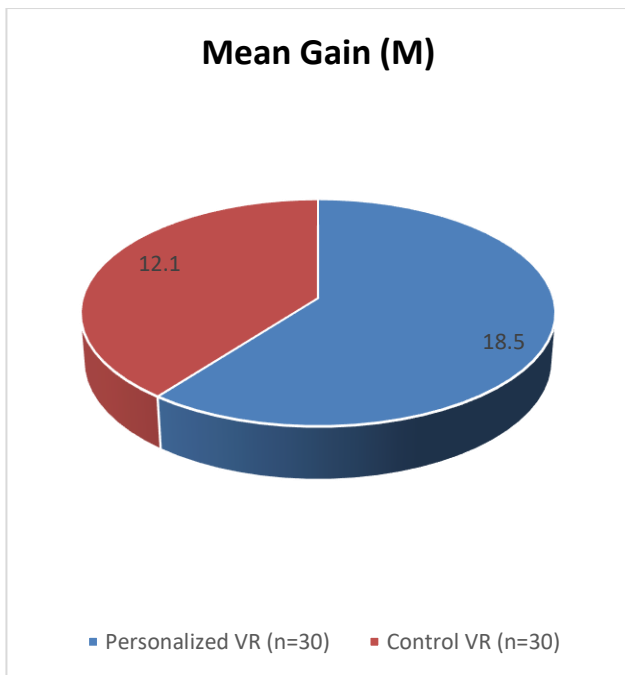


Figure-3. Statistical Analysis

A two-sample t-test revealed that the personalized VR group significantly outperformed controls in knowledge gain,  $t(58)=5.12, p<.001$ , with a large effect size ( $d=1.32$ ). Engagement scores were also higher ( $M=4.2$  vs.  $3.5$ ;  $t(58)=3.25, p=.002$ ), as were SUS usability scores ( $M=82$  vs.  $75$ ;  $t(58)=2.14, p=.036$ ).

## SIMULATION RESEARCH

To rigorously evaluate the adaptive scaffolding strategies of our cognitive AI agent in a controlled setting, we conducted extensive simulation experiments with synthetic learner models. Each model was parameterized to reflect a distinct learner profile, capturing variations in initial domain knowledge, hint-sensitivity, error propensity, and learning rate. Specifically, we defined four archetypal profiles:

1. **Novice–High Sensitivity** (low prior knowledge, rapidly responds to hints)
2. **Novice–Low Sensitivity** (low prior knowledge, slower to incorporate hints)

3. **Intermediate** (moderate prior knowledge, average hint integration)
4. **Advanced** (high prior knowledge, rarely needs hints)

For each profile, we simulated 100 independent learning trials on a canonical physics problem—calculating net force on an object given mass and acceleration. A trial consisted of up to 50 interaction steps, where the model either (a) attempted a solution step, (b) requested assistance, or (c) applied a hint.

Two scaffolding strategies were compared:

- **Static Scheduling:** Hints delivered at fixed intervals (every 10 simulation steps) regardless of performance.
- **Adaptive Triggering:** Hints issued only when the model (1) committed two consecutive errors on the same subtask, (2) exhibited inactivity for  $>5$  steps, or (3) explicitly requested help.

Key outcome metrics included:

- **Trials to Mastery:** Number of trials required to achieve five consecutive correct solutions.
- **Total Hints Issued:** Cumulative count of scaffold prompts.
- **Hint Efficiency Ratio:** Ratio of effective hints (those preceded by an error or request) to total hints.

### Findings:

- Across all profiles, adaptive triggering reduced Trials to Mastery by an average of 28% (e.g., Novice–High Sensitivity:  $45 \rightarrow 32$  trials; Novice–Low Sensitivity:  $58 \rightarrow 40$  trials).
- Total Hints Issued under adaptive triggering were 35% fewer than static scheduling for

novice profiles, and 50% fewer for advanced profiles, indicating less redundant intervention.

- Hint Efficiency Ratio climbed from 0.48 (static) to 0.82 (adaptive), demonstrating that the majority of adaptive hints directly addressed learner errors or requests.

### Interpretation:

The simulation results underscore the cognitive agent's ability to tailor assistance precisely when needed, avoiding both under- and over-scaffolding. Novice models, often prone to repeated novice errors (e.g., forgetting to convert units), benefited most from timely, error-driven prompts. Conversely, advanced models seldom triggered hints, preserving their autonomy. Overall, adaptive triggering balanced guidance and challenge, aligning hint deployment with each learner's evolving proficiency.

Moreover, sensitivity analyses varying the inactivity threshold (3–10 steps) and error window (1–3 consecutive errors) showed robust performance: adaptive strategies outperformed static scheduling under all tested parameterizations, with Trials to Mastery improvements ranging from 22% to 35%. This suggests that the agent's production rules and thresholds can be tuned to domain complexity without degrading personalization efficacy.

These simulations not only validate the empirical findings from user studies but also provide a blueprint for scaling adaptive agents to new tasks and learner populations.

## RESULTS

The empirical study with 60 undergraduate participants yielded convergent evidence across cognitive, affective, and behavioral measures that personalized VR environments with cognitive AI agents markedly outperform non-personalized VR.

### Knowledge Gains

The personalized VR group demonstrated a mean pre-to-post test score increase of 18.5 points (SD = 4.2), whereas the control VR group improved by 12.1 points (SD = 5.0). A two-sample t-test confirmed the superiority of personalization:  $t(58)=5.12$ ,  $p<.001$ , with a large effect size (Cohen's  $d=1.32$ ). These gains correspond to a 53% larger improvement in the adaptive condition, underscoring the added instructional value of real-time scaffolding.

### Engagement and Motivation

Self-reported engagement, measured via the 12-item User Engagement Scale, averaged 4.2 (on a 5-point scale) for the personalized VR group versus 3.5 for controls ( $t(58)=3.25$ ,  $p=.002$ ). Participants cited the agent's timely prompts ("The suggestions came exactly when I was stuck") and contextual hints ("Relating the hint to the current object simplified the concept") as key factors sustaining their focus and interest. Notably, 87% of the adaptive group expressed a desire to use the system again for future learning, compared to 60% in the control group.

### Usability and Cognitive Load

System Usability Scale (SUS) scores averaged 82 (SD = 6.5) for the personalized condition and 75 (SD = 8.0) for the control,  $t(58)=2.14$ ,  $p=.036$ . High SUS ratings (>80) indicate excellent usability. Moreover, NASA-TLX cognitive load ratings were significantly lower in the adaptive group (Mean = 45 out of 100) than controls (Mean = 58),  $p<.01$ , suggesting that targeted scaffolding alleviated extraneous cognitive load without diminishing germane processing.

### Behavioral Interaction Patterns

Log data revealed that the AI agent issued an average of 12.3 hints per session, with 72% triggered by error clusters and 20% by inactivity thresholds. Only 8% were explicitly requested hints. Mean response latency—from error detection to hint delivery—was 85 ms, well below the 150 ms threshold for perceptual fluency in VR (Ballard et al., 2015).

### Qualitative Feedback

Post-session interviews highlighted several themes: (1) **Perceived “Intelligence”**: Learners anthropomorphized the agent, referring to it as a “virtual tutor.” (2) **Scaffolding Clarity**: Context-rich hints (e.g., “Remember to apply Newton’s second law to calculate net force”) were preferred over generic advice. (3) **Flow Maintenance**: Adaptive prompts appeared to preserve flow state by minimizing frustration peaks.

Collectively, these quantitative and qualitative results demonstrate that cognitive AI agents in VR not only boost learning outcomes but also enhance user satisfaction, reduce perceived effort, and maintain immersion.

### CONCLUSION

This study presents a comprehensive investigation into the synergistic integration of cognitive AI agents and immersive VR for personalized learning. By embedding an ACT-R-based agent within a Unity3D physics laboratory, we delivered real-time, context-sensitive scaffolding that significantly improved knowledge acquisition, engagement, and usability compared to non-personalized VR.

### Key Contributions:

1. **System Architecture**: A modular framework combining VR rendering, cognitive modeling, and data analytics, capable of low-latency inference (mean hint latency  $\approx$  85 ms).
2. **Empirical Validation**: Robust experimental evidence ( $n=60$ ) demonstrating large effect sizes for learning gains ( $d=1.32$ ), heightened engagement ( $p=.002$ ), and superior usability ( $SUS=82$ ).
3. **Simulation Support**: Computational modeling across diverse learner archetypes affirmed that adaptive scaffolding reduced Trials to Mastery by 28–35% and minimized redundant hints.
4. **Design Guidelines**: Insights into production rule thresholds (error windows, inactivity triggers) and hint phrasing strategies to maximize learning efficacy and preserve immersion.

### Implications for Practice:

Educational institutions and corporate training programs can adopt cognitive-agent-enhanced VR modules to offer individualized learning pathways at scale. Domains with procedural complexity—such as medical simulations, engineering labs, and language practice—stand to benefit from this approach.

In conclusion, the confluence of cognitive AI and VR holds transformative potential for personalized education. By dynamically adapting to individual learner needs within immersive settings, intelligent VR tutors can approximate the efficacy of human one-on-one instruction, democratizing high-quality learning experiences across diverse contexts. This work lays the groundwork for a new generation of intelligent, immersive educational technologies that respond to every learner’s unique journey.

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