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Research Article

The Llama–ARCS Adaptive Learning framework: AI–VR Integration System for Real-Time Motivational Feedback in Higher Education

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Abstract: This study developed and evaluated an AI-integrated Virtual Reality (VR) system designed to enhance personalized learning in higher education. While VR improves engagement, existing systems often lack adaptivity or experience high latency during AI interactions. To address these limitations, this research introduces a novel integration of a cache-optimized Llama 2 Large Language Model (LLM) that delivers real-time, motivationally grounded feedback. The system was implemented using Unity 3D and validated with 50 undergraduate students. Technical validation showed that the cache layer reduced interaction latency from 17.7 ms to 14.2 ms and maintained zero system crashes throughout the pilot. Learner motivation was assessed using Keller's ARCS model, yielding mean scores ranging from 4.08 to 4.69 across all dimensions. Independent t-tests ($p > 0.05$) and negligible effect sizes (Cohen's $d < 0.2$) revealed no significant difference between technical (ICT) and non-technical (Physics) students. These findings confirm that the proposed system effectively bridges technological and motivational gaps, providing a robust model for adaptive, immersive education.

Keywords: Adaptive Learning; Artificial Intelligence; Higher Education; Learning Analytics; Llama–ARCS; Motivational Theory; Real-Time Feedback; Virtual Reality.

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1. Introduction

Virtual Reality (VR) is gaining wider use in education because it supports immersive, interactive learning experiences that extend beyond traditional instruction. Students can observe concepts in three dimensions, interact with simulated objects, and engage in tasks that strengthen focus, comprehension, and retention [1]. These capabilities make VR a valuable tool for teaching abstract ideas in science, technology, engineering, and mathematics, where learners often struggle with visualization and conceptual complexity [2]. VR environments also support multisensory learning by integrating visual, auditory, and kinesthetic cues, benefiting students with diverse learning needs, including those with learning difficulties or disabilities.

Earlier studies explored VR as a medium for laboratory simulations, virtual field trips, and remote teaching, especially during the COVID-19 disruption [3], [4]. These studies relied on fixed, non-adaptive VR applications that presented the same content to every learner. They offered useful experiential learning but lacked mechanisms for real-time personalization. As a result, learners who required additional guidance did not receive targeted support, while advanced learners experienced unnecessary repetition [5], [6].

More recent research has investigated AI-driven VR systems that integrate large language models (LLMs) into virtual environments. Study [7] introduced an LLM-based non-playable character capable of conversation and multimodal guidance. Their findings showed improved engagement, yet two major weaknesses remained: high processing load and response delays. These limitations hindered interactivity and reduced immersion during learning activities.

In summary, existing AI–VR systems face two main challenges: slow response time and limited personalization. This study introduces a cache-optimized Llama 2 model to address these issues and integrates motivational design principles through Keller's ARCS framework. The proposed framework aims to operationalize motivational theory within an adaptive AI–VR architecture, providing real-time personalized feedback to enhance learner engagement and motivation. The remainder of this paper is structured as follows: Section 2 reviews related studies on AI–VR integration and motivational learning models; Section 3 presents the proposed Llama–ARCS framework and system implementation; Section 4 discusses the evaluation methods and results; Section 5 compares the findings with prior work; and Section 6 concludes the paper with implications and directions for future research.

2. Literature Review

2.1. Artificial Intelligence (AI) in the classroom

Artificial Intelligence (AI) is fundamentally transforming classroom instruction by optimizing both pedagogical and administrative processes. Systematic reviews demonstrate that AI enables systems, ranging from chatbots to specialized tutoring algorithms, to perform tasks that require human-like cognitive abilities, such as adaptation and decision-making. Educational institutions have increasingly integrated these technologies to improve instructional delivery; teachers report enhanced productivity in grading and lesson preparation, while students benefit from content tailored to their specific learning needs [8]. The adaptability of AI systems has been empirically shown to foster greater learner engagement, improve retention, and enhance overall instructional quality[9].

The evolution of AI in education has progressed from early computer-based instruction to sophisticated Intelligent Tutoring Systems (ITS) and humanoid robots, reshaping educational paradigms. These systems assist instructors by enabling adaptive curriculum design that meets diverse learner needs [10]. However, recent practices demonstrate that AI is most effective when it complements human instruction rather than replacing it. For example, study [11] documented how teachers utilize AI tools primarily for formative assessment and adjusting reading levels, showcasing its strength as a supportive instructional tool.

In the specific context of Nigeria, study [12] analyzed emerging trends in AI adoption within higher education. While they found promising uses in predicting student performance, they observed a significant research and implementation gap in advanced intelligent tutoring systems and adaptive technologies. Their research emphasized that greater investment is critically needed to strengthen AI integration in Nigerian higher education. This identified gap, specifically the lack of adaptive, intelligent systems in local educational contexts, serves as a primary motivation for the development of the AI-integrated framework proposed in this study.

2.2. Virtual Reality (VR) in the Classroom

Virtual Reality (VR) and Augmented Reality (AR) have emerged as critical tools for creating immersive and interactive learning experiences. These technologies simulate real-world environments, enabling students to explore, interact with, and engage with content in ways that traditional didactic methods cannot [13]. Study [14] conducted a comprehensive twelve-year review of AR and VR developments in education, analysing 1,536 articles retrieved from the Scopus database through text mining and topic modelling. Their findings revealed an exponential increase in the adoption of AR and VR technologies, particularly via wearable devices. However, they identified that while these technologies significantly improve engagement and simulation-based learning, integration in schools remains slow due to high implementation costs, limited institutional capacity, and a lack of content customization a limitation that AI integration aims to address.

Building on this, research [15] utilized a systematic review and bibliometric analysis (PRISMA) to examine AR and VR applications in online education. Their study highlighted that these technologies contribute substantially to teaching across diverse disciplines, such as engineering, medicine, nursing, and chemistry. The research underscores that AR and VR can serve as cost-effective, scalable tools for global online learning, provided educational institutions invest in appropriate infrastructure. Collectively, these studies affirm that while immersive technologies enhance engagement and experiential learning, persistent gaps in customization and teacher readiness remain barriers that must be addressed to leverage VR's potential in the classroom fully.

2.3. Review of Related Works

Several studies have examined the use of immersive technologies in education without direct AI integration. Research [16] conducted a systematic literature review of studies from 2020 to 2025 and found that VR applications enhance engagement, retention, and accessibility, though cost and ethical challenges persist. The study emphasized the need for empirical validation and long-term research linking immersive technologies to measurable motivation and performance outcomes. Similarly, a study [17] that conducted a scoping and thematic review of 36 studies reported that immersive technologies improve engagement and collaboration but noted that teacher readiness often limits adoption. They recommended further evaluation of AI-driven adaptivity and inclusive learning design to maximize effectiveness.

A significant body of literature has also explored the integration of AI with immersive technologies. Almeman et al. [18] conducted a PRISMA-based systematic review analyzing AI-Metaverse integration, demonstrating that such systems enable adaptive learning and personalized tutoring across disciplines. However, they found that most studies remained conceptual, with limited real-world data on learner motivation or performance metrics. Similarly, Wang et al. [19] highlighted the benefits of adaptive AI in education through bibliometric analysis, yet motivational measures were notably absent. Study [20] reviewed 139 studies on AI, VR, and LLM applications in special education, reporting positive effects on engagement and cognitive development but recommending the creation of standardized frameworks for motivational and cognitive evaluation. Mustafa et al. [21] further emphasized the potential of AI–VR for intelligent tutoring systems but identified a key gap in the limited focus on inclusive and motivational outcomes.

Recent technical frameworks have focused on optimizing AI–VR integration, though significant challenges remain regarding latency and empirical validation. El Hajji et al. [7] proposed a robust architecture for intelligent tutoring in VR that integrates LLM-based non-playable characters (NPCs) with multimodal feedback. In their performance evaluation, they reported generally stable rendering latency, with average start-up times of 21.58s (desktop) and 20.36s (Meta Quest 3). However, they explicitly identified conversational latency as a persistent bottleneck. Their metrics indicated that Text-to-Speech (TTS) processing required approximately 10s, with an additional 2s for Speech-to-Text (STT) transcription. These delays, including a 2s freeze at the start of recording, temporarily disrupted the real-time flow of interaction. While their study demonstrated that AI-driven VR tutoring can operate stably, the unresolved speech processing latency underscores the need for optimized retrieval mechanisms, such as the cache layer introduced in this study, to ensure real-time dialogue responsiveness.

In contrast to interaction-focused systems, Duan et al. [22] concentrated on environmental generation using the LatticeWorld framework. By combining Llama 2 and Unreal Engine 5, they achieved a 90× increase in scene generation efficiency. However, their work was purely technical and lacked assessment of educational outcomes or learner motivation. Similarly, Haynes [23] introduced the "Crazy Slots" architecture for teacher training, employing a Retrieval-Augmented Generation (RAG) database to generate authentic student responses. Although the framework offers a scalable approach to minimizing computational cost, it has not yet been experimentally validated. It lacks metrics on learner motivation, representing a critical area for future research.

While technical frameworks exist, empirical validation of learner outcomes remains limited. Tobias et al. [24] provided one of the few empirical studies examining AI–VR-enhanced ethical training. Comparing an immersive AI/VR group with a traditional role-play control group (N = 60), they found that the AI/VR group demonstrated significantly greater improvement in ethical competence, particularly in consequence analysis. However, the authors noted that further research is needed to explore broader applicability across disciplines. Song et al. [25] developed LearningverseVR, a game-based platform leveraging generative AI for dynamic NPC interactions. Although the system represents promising efforts to integrate intelligent agents within virtual learning environments, it still faces challenges related to real-time adaptivity, multimodal interaction, and flexible deployment. While such platforms demonstrate potential for situated learning, most remain design-oriented and offer theoretical arguments for personalization with limited empirical validation. Study [26] did report significant improvements in student motivation using VR; however, their study did not incorporate AI-driven adaptivity.

Collectively, the reviewed studies demonstrate consistent benefits of immersive technologies in enhancing engagement but reveal persistent limitations in adaptivity, latency management, and motivational evaluation. Even advanced AI–VR frameworks, such as those in reference [7], achieved lower interaction latency but failed to report learning or motivational outcomes, leaving major questions about pedagogical effectiveness unanswered. Therefore, a critical research gap remains in developing AI-driven VR environments that dynamically adapt to learner behavior, optimize computational performance, and are empirically validated through established motivational frameworks such as Keller's ARCS model. Addressing this gap is the central contribution of the Llama–ARCS Adaptive Learning Framework proposed in this study.

3. Proposed Method

3.1. Participants

The target population comprised final-semester students from the Departments of Physics and ICT at the Air Force Institute of Technology, Kaduna. Using purposive sampling, 50 participants were selected, 25 from each department, all of whom had prior experience using a computer.

3.2. Methodological Framework

This study is anchored on the Llama–ARCS Adaptive Learning System, a methodological structure that defines how the VR environment was developed, how adaptive AI feedback was generated, and how learner motivation was evaluated after the learning experience. The framework clarifies the interrelationship between system components and ensures that both the technical and educational objectives of the study are addressed coherently. The overall structure of this framework is illustrated in Figure 1.

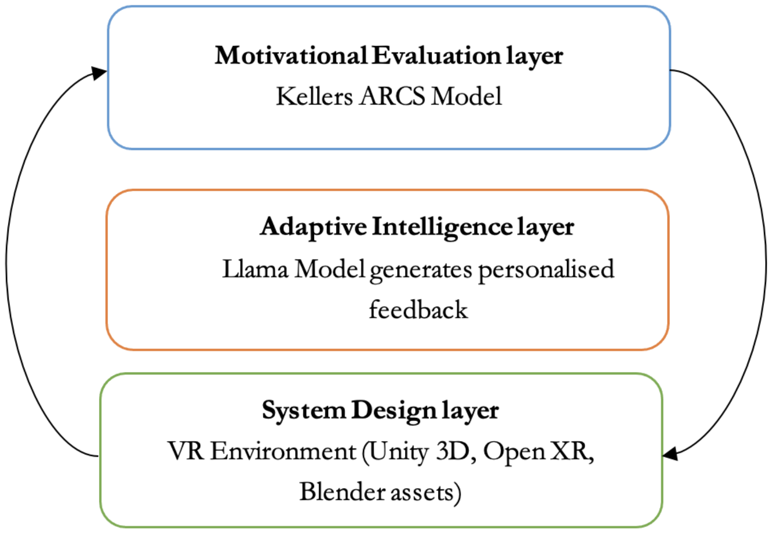

Figure 1. The Llama–ARCS adaptive learning framework

The first layer, the System Design Layer, focuses on creating the immersive VR learning environment. This includes developing interactive 3D scenes, laboratory tasks, and instructional elements using Unity 3D and OpenXR. Within this environment, students engage with objects, navigate the space, and perform learning activities that mirror real-world procedures. The system records key interactions, such as object manipulation, task completion patterns, and navigation behavior, providing the contextual data the AI tutor needs to respond meaningfully.

The second layer, the Adaptive Intelligence Layer, represents the AI component of the system. In this layer, the Llama model processes student queries and generates real-time, context-aware feedback based on learner actions inside the virtual environment. The model delivers explanations, clarifications, and guidance aligned with each learner's trajectory. A cache-optimization mechanism is integrated into this layer to reduce latency and maintain smooth interaction, ensuring that frequently repeated queries receive instantaneous responses. This layer operates entirely within the VR environment, providing adaptive support during the learning session.

The third layer, the Motivational Evaluation Layer, operates outside the VR environment and is administered after the learning session concludes. This layer applies Keller's ARCS model as a post-test instrument to determine whether the system experience sustained learner motivation. The evaluation assesses four constructs—Attention, Relevance, Confidence, and Satisfaction—using a structured questionnaire administered through the Socrative platform. Importantly, this layer does not influence the AI tutor or the VR system; instead, it provides an independent measure of the system's motivational impact.

Together, these three layers form a coherent methodological structure that connects system design, adaptive intelligence, and post-experience motivational evaluation. The framework supports both the technical development of the AI–VR learning system and the empirical assessment of its educational impact, ensuring that the study evaluates not only how the system functions but also how it influences learner motivation.

3.2.1. System Components

The core of the system is built around the Unity game engine. This platform integrates 3D assets created in Blender—including 3D models, animations, and textures—with the VR components via the OpenXR Plugin to ensure headset compatibility. The adaptive component is powered by the Llama Model (Hugging Face Transformers). The overall system workflow is illustrated in Figure 2. The process operates as follows:

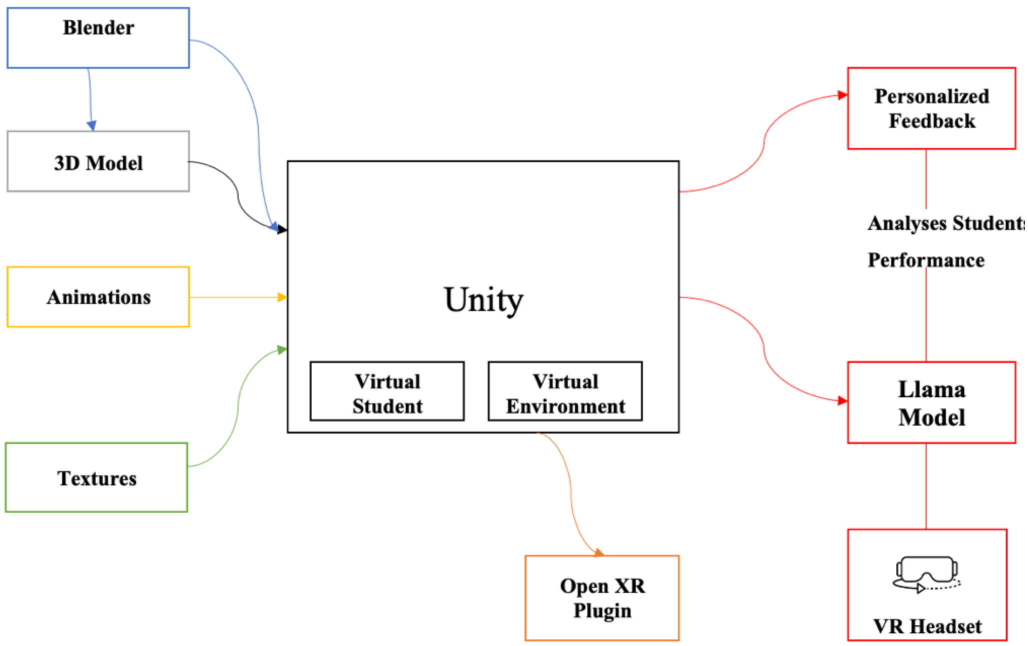

Figure 2. System components of the AI-Integrated VR learning platform

The system captures student input during interactions within the Virtual Environment. This data—representing learning patterns and performance behavior—is sent to the AI Engine for processing. The Llama Model generates personalized feedback and adaptive recommendations tailored to the learner's context. The feedback is delivered to the learner through the Virtual Student, an AI-animated 3D avatar that provides real-time interaction and guidance.

3.3. Cache Optimization Strategy

To improve real-time performance, the system architecture introduces a Cache Layer positioned between user input and the Llama 2 Model to optimize inference time. As illustrated in Figure 3, the process operates through two distinct paths:

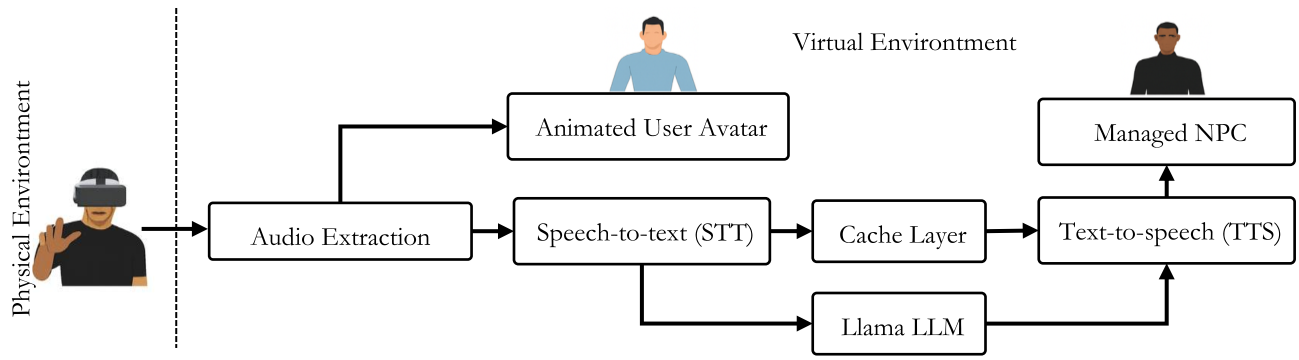

Figure 3. Improved system architecture of the AI-Integrated VR system with cache layer

Fast Path (Cache Hit): If a learner's query (Q) already exists in the cache, the corresponding response (R) is retrieved instantly, bypassing the LLM computation. Slow Path (Cache Miss): If the query is new, it is processed by the Llama 2 Model to generate a response. The new response is then stored in the cache for future retrieval, thereby minimizing latency in subsequent interactions. This cache optimization strategy ensures that frequent or repetitive learner queries are handled instantaneously, maintaining the system's conversational flow and immersive quality during VR learning sessions.

3.4. Technical Implementation

To ensure reproducibility, the specific configurations for the AI and VR components are detailed below.

3.4.1. Llama Model Configuration

The system utilizes the pre-trained Meta Llama 2 7B HF model. It was not fine-tuned; instead, it was deployed using a Retrieval-Augmented Generation (RAG) approach via prompts to ensure generalized knowledge retrieval. To balance creativity with accuracy, the model was configured with a temperature of 0.7, a max_new_tokens limit of 512, and a repetition_penalty of 1.1. Additionally, a custom Cache Layer intercepts queries to reduce inference latency and optimize response time, as illustrated in Figure 4.

3.4.2. VR Hardware and Interaction

The study utilized the Meta Quest 2 headset as the primary hardware for immersive learning. The system used the OpenXR Plugin, which ensures cross-platform compatibility across different VR devices. The interaction design was developed to simulate realistic learning experiences by enabling students to manipulate objects with a controller using XRGrabInteractable, allowing them to grab, move, and interact with virtual elements. Additionally, Ray Interactors were implemented to enable intuitive UI and quiz selection within the environment, supporting both gesture-based and gaze-based engagement. This configuration ensured smooth and responsive interaction between learners and the virtual environment while maintaining usability across sessions.

3.5. Technologies and Implementation

The system was developed using Unity 3D for the virtual environment and C# for logic scripting. Communication with the AI backend was handled through a local FastAPI server. A custom cache manager using a high-speed key-value store was implemented to manage query matching efficiently. The hardware setup included a Meta Quest 2 headset and a workstation equipped with an Intel Core i7 processor and 16 GB of RAM. This configuration ensured stable performance during immersive learning sessions and supported real-time adaptive feedback generation.

3.6. Instrumentation

The instrument used was an adaptation of the Instructional Materials Motivation Survey (IMMS) based on Keller's ARCS model [27], which includes four study dimensions: (1) Attention, captured through situations that surprise students; (2) Relevance, assessed when students consider the materials valuable for their learning process; (3) Confidence, reflected in students' expectations of success; and (4) Satisfaction, experienced when students feel that the outcome of their effort meets their expectations.

The instrument consisted of 36 Likert-scale questions, divided as follows: 12 for Attention, 9 for Relevance, 9 for Confidence, and 6 for Satisfaction. It was administered at the end of the immersive experience using the Socrative application. The reliability of the instrument was validated using Cronbach's Alpha coefficients. These were calculated for each subscale: Attention ($\alpha = 0.75$), Relevance ($\alpha = 0.73$), and Satisfaction ($\alpha = 0.72$). The Confidence subscale initially showed low consistency ($\alpha = 0.35$); however, after removing reverse-coded items (C3, C6, C8), reliability improved to $\alpha = 0.77$.

3.7. Algorithm

The response generation logic is defined in Algorithm 1. The system prioritizes cache look-up operations to minimize latency, an essential factor for maintaining immersion and continuity during VR learning sessions.

Algorithm 1. Response generation with a cache layer

```
INPUT: Learner query Q
OUTPUT: AI-generated feedback R
# Initialization:
Initialize the Llama model for inference.
Define VR environment settings and NPC roles.

# Initialize Cache Layer (to store previously computed queries and responses).
Response Generation:
Receive learner query Q.
Check cache for Q:
    If Q exists (Cache Hit) → Retrieve R from cache.
    Else (Cache Miss):
        Decompose Q into subcomponents if complex.
        Forward Q to the Llama LLM for inference.
        Generate and aggregate subcomponent responses into a full response R.
        If R is non-user-specific (static knowledge or definition), store (Q, R) in cache for future retrieval.

#Structure R (Enhancement):
    Pose reflective follow-up questions to stimulate critical thinking.
    Summarize key concepts and verify learner understanding.

Send R to the VR system.
Display R to the learner through the AI avatar interface.

End.
```

3.8. Description of the Educational Experience

The study utilized a 20-minute immersive session conducted on the Meta Quest 2 headset. Developed in Unity 3D, the environment comprised two primary spaces: a Virtual Classroom for instructional delivery and learning profile management, and a Virtual Laboratory for simulating realistic scientific experiments. Students interacted with the environment using the XR Interaction Toolkit, which enabled them to manipulate 3D objects with hand controllers physically. The overall learning setup and student interaction process are illustrated in Figure 4.

The core educational feature was the Adaptive AI Tutor, powered by Llama 2, that provided real-time, context-aware responses to student queries about experimental procedures. The session incorporated adaptive guidance that dynamically responded to learners' actions and progress. The immersive experience concluded with an adaptive quiz that analyzed student performance to generate personalized corrective feedback, ensuring that the session remained responsive to individual learning needs. This process allowed continuous adaptation between learner input and system feedback, maintaining engagement and motivation throughout the session.

Figure 4. Students interacting with the AI–VR system

4. Results and Discussion

This section presents the empirical findings obtained from the development and validation of the AI-integrated VR system. The results are categorized into three key areas: (1) the functional system outputs and interface design, (2) the technical performance metrics assessing the efficiency of cache-layer optimization, and (3) the educational validation of learner motivation using descriptive and inferential statistics based on Keller's ARCS model. These results are subsequently analyzed to interpret the system's impact on enhancing personalized learning experiences and optimizing technical latency.

4.1. System Output

The system output demonstrates how students and instructors interacted within the AI–VR environment. The developed platform included two interconnected spaces—a Virtual Classroom for instructional delivery and a Virtual Laboratory for simulated experimentation. The system enabled real-time adaptive feedback, allowing learners to engage with virtual objects, receive AI-generated guidance, and perform experimental tasks under instructor supervision. The immersive environment, developed in Unity 3D, is shown in Figure 5, illustrating both student perspectives and the instructor view within the virtual classroom.

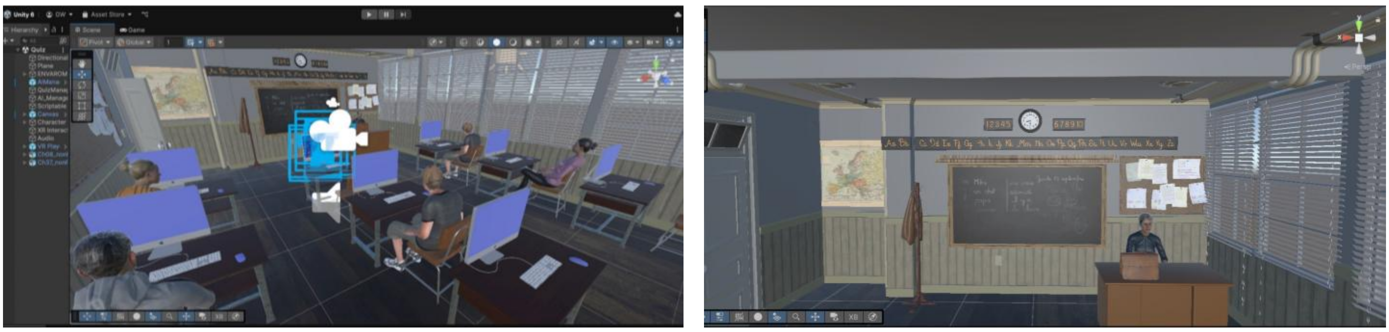

Figure 5. Students in the virtual classroom

4.2. Technical Validation

The cache layer significantly improved system performance. Interaction latency decreased from 17.7 ms (baseline) to 14.2 ms with the cache mechanism enabled. Furthermore, system stability improved from occasional crashes to zero crashes during the pilot testing phase. As illustrated in Figure 6, the real-time console log confirms successful execution of Cache Hit and Cache Miss operations, including the automatic storage of new entries and live calculation of the Hit Rate. These observations directly validate the optimization mechanism that reduces interaction latency and maintains smooth performance during real-time interaction in VR.

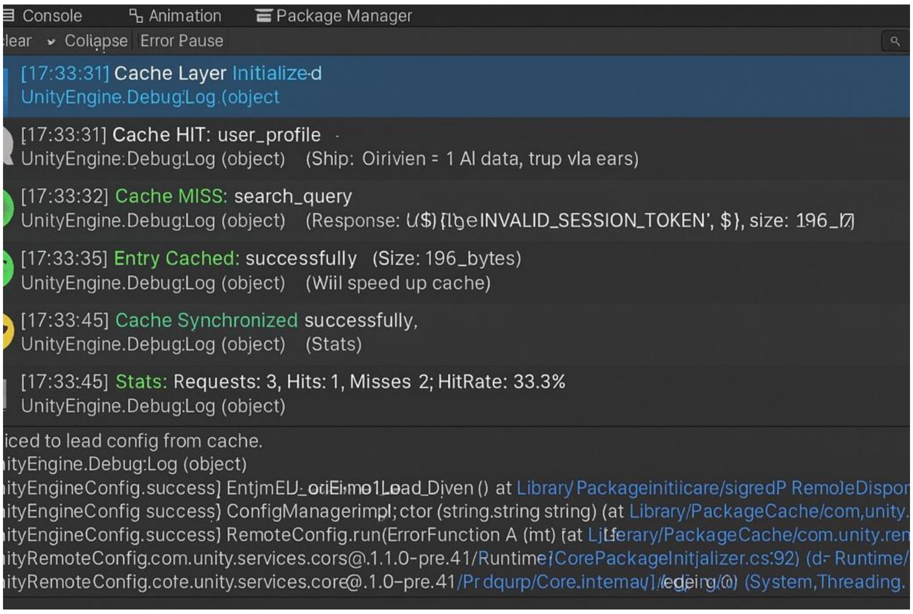

Figure 6. Real-Time console log for cache layer operation (hits, misses, and hit rate)

4.3. Motivational Outcomes

As summarized in Table 1, the comparative analysis of motivational outcomes indicates that the system was equally effective for both technical (ICT) and non-technical (Physics) student groups. Both groups reported high mean scores across all four motivational dimensions, with Relevance and Satisfaction achieving the highest averages (Mean > 4.5). Although ICT students recorded slightly higher mean scores for Attention (4.19) than Physics students (4.08), the visual distribution in Figure 7 and subsequent statistical testing confirmed that these differences were negligible.

This consistency suggests that the AI-integrated VR system effectively bridged the gap between learners of different academic backgrounds, maintaining comparable levels of engagement and motivation regardless of prior technical experience.

Table 1. Results by Dimension for the Physics and ICT Courses.

Dimension	Department	Mean	Std. Dev	Positive Percentage (≥ 4.0)
Attention	ICT	4.19	0.73	76.0%
	Physics	4.08	0.61	68.0%
Relevance	ICT	4.69	0.39	92.0%
	Physics	4.67	0.31	96.0%
Confidence	ICT	4.44	0.52	80.0%
	Physics	4.33	0.68	72.0%
Satisfaction	ICT	4.65	0.52	92.0%
	Physics	4.55	0.52	96.0%

4.4. Inferential Statistics

To determine whether academic background influenced student motivation, an independent-samples t-test was conducted to compare responses from students in the Physics (non-technical) and ICT (technical) courses. As shown in Table 2, no statistically significant differences were observed across any of the four ARCS dimensions ($p > 0.05$). While ICT students recorded marginally higher mean scores in Attention (4.190 vs. 4.077) and Confidence (4.440 vs. 4.326), the t-statistics (0.593 and 0.668, respectively) and high p-values indicate that these differences were not statistically meaningful. The calculated Cohen's d effect sizes for all dimensions were below 0.2, signifying negligible effects. These findings suggest that the AI-integrated VR system was equally effective in fostering learner motivation across disciplines, regardless of prior technical expertise.

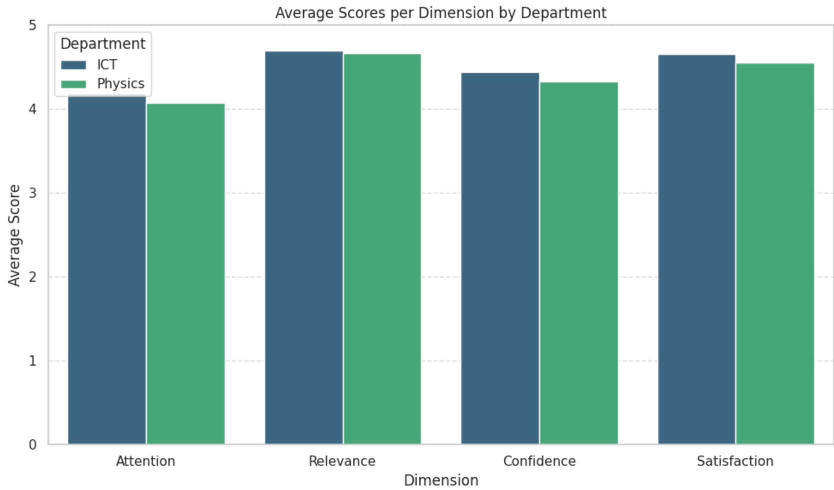

Figure 7. Comparative analysis of motivational results by dimension (attention, relevance, confidence, satisfaction) for physics and ICT courses.

Table 2. Independent samples t-test comparing physics and ICT student responses.

Dimension	ICT Mean	Physics Mean	t-statistic	p-value	Cohen's d
Attention	4.190	4.077	0.593	0.556	0.168
Relevance	4.693	4.667	0.267	0.791	0.075
Confidence	4.440	4.326	0.668	0.508	0.189
Satisfaction	4.653	4.553	0.677	0.502	0.191

4.5. Discussion

The findings of this study clearly demonstrate that the developed AI-integrated Virtual Reality system positively influenced student motivation, effectively aligning with the constructs of Keller's ARCS model. Students from both the Physics and ICT departments reported consistently favorable responses, underscoring the system's capacity to deliver a high-quality and engaging learning experience. These results are consistent with previous studies highlighting the motivational potential of immersive learning environments in higher education [26].

The highest mean scores were observed in the Relevance (Mean = 4.69) and Satisfaction (Mean = 4.65) dimensions, as shown in Table 1 and Figure 6. These outcomes indicate the system's success in delivering content that students found meaningful and enjoyable. Relevance emerged as a particular strength, with both Physics and ICT students reporting very high scores, with the Physics group reaching 96.0% positive responses. This finding suggests that the AI-generated feedback was effectively tailored to the learners' academic goals and needs, reinforcing Keller's principle that motivation is maximized when learning materials are perceived as meaningful and goal-oriented. The system's ability to contextualize core physics concepts through personalized AI-driven dialogue was a crucial factor in fostering this sense of relevance.

High satisfaction scores are directly linked to the system's technical performance and architectural efficiency. This effect correlates with the cache mechanism described in Section 3.3, which successfully minimized interaction latency to 14.2 ms by handling static, generalized queries (Cache Hits) instantaneously. This optimization prevented the conversational lag commonly reported in earlier LLM–VR systems [7]. Consequently, the cache system allowed the Llama model to allocate full computational resources to personalized, context-aware responses (Cache Misses), as defined in Algorithm 1. This ensured that adaptive dialogue occurred seamlessly within the immersive flow, thereby strengthening user engagement. The cache layer, therefore, served as a foundational technical feature contributing to the high Satisfaction scores observed across both groups.

Although Attention scores (Mean = 4.29) were slightly lower than Relevance and Satisfaction, they remained positive and represent a fundamental component of the ARCS framework. The VR system's ability to simulate realistic laboratory scenarios effectively captured attention initially. The integration of the Llama model sustained this engagement by providing personalized, responsive feedback, maintaining learners' focus throughout the short intervention.

The Confidence dimension (Mean = 4.14) also yielded generally strong results, though it warrants methodological consideration. The initial reliability analysis of the Confidence subscale showed low internal consistency ($\propto = 0.35$), prompting the removal of specific reverse-coded items. This issue likely stemmed from students' difficulty in accurately self-assessing their confidence immediately after an engaging, novel immersive experience. Future applications of this framework should consider simplifying or phrasing the assessment items more positively to improve clarity and reliability in post-intervention evaluations. The presence of neutral responses suggests that while the system was highly usable, some students—particularly those less experienced with VR—may require additional orientation sessions to build self-assurance.

The comparative analysis of the two groups yields one of the study's most significant findings. The independent t-tests (see Table 2) showed $p > 0.05$ and negligible effect sizes (Cohen's $d < 0.2$) across all four ARCS dimensions, confirming that the system's motivational impact was statistically equivalent between Physics and ICT students. This consistency provides strong validation of the system's user experience (UX) design. Notably, the Physics group—typically less familiar with advanced digital tools, reported levels of Confidence and Satisfaction that were statistically equivalent to those of the ICT group. This demonstrates that the system's intuitive interface and optimized technical performance successfully mitigated the technological gap between technical and non-technical learners. However, the Physics cohort exhibited slightly higher variability in Confidence (SD = 0.68 compared to 0.52 for ICT), indicating that while most participants responded positively, some non-technical students experienced greater uncertainty. This finding highlights the potential value of pre-session familiarization or guided tutorials for non-ICT participants to promote consistent confidence levels.

Beyond technical performance, this study reinforces an important insight for AI-based educational system design: system speed is a key motivational factor. The high Satisfaction and Relevance scores confirm that minimizing latency and response delay sustains learner engagement and focus. Low-latency engineering should therefore be regarded not merely as a technical optimization but as a pedagogical necessity for effective immersive instruction.

The main limitation of this study lies in its reliance on a single, short-term intervention lasting approximately 20 minutes. Motivation levels may be temporarily elevated due to the novelty effect of new technology. Consequently, longitudinal research is needed to determine whether these motivational gains can be sustained across extended learning periods, such as over a semester. Furthermore, future work should investigate the direct relationship between AI-generated adaptive feedback and measurable cognitive learning outcomes (e.g., performance scores or retention tests). Establishing this connection would strengthen the educational validity of the proposed system, extending its significance beyond motivational impact.

5. Comparison

To highlight the distinct contributions of the Llama–ARCS framework, this study compares its architectural performance and pedagogical outcomes with several recent state-of-the-art AI and VR learning systems. As summarized in Table 3, the comparison focuses on three key dimensions: AI integration, technical optimization (latency), and empirical validation of learner motivation. The most direct point of reference is the system proposed by [7], which integrated LLMs into VR environments for intelligent tutoring. Although their system maintained stable rendering frame rates, it experienced considerable conversational latency—up to 12 seconds per full processing cycle—creating a bottleneck that disrupted the immersive learning flow. In contrast, the proposed Llama–ARCS framework incorporates a dedicated Cache Layer, which significantly optimized interaction latency. This mechanism reduced the latency from a baseline of 17.7 ms to 14.2 ms and completely eliminated system crashes by offloading repetitive queries from the LLM. These results validate that caching provides an effective solution to the latency issues identified in earlier generative AI–VR systems.

Furthermore, this study extends prior work by integrating adaptive AI feedback, latency optimization, and motivational validation within a single experimental framework. To contextualize these outcomes, a descriptive comparison was conducted against the findings of

[26], who evaluated a non-adaptive VR system. While their study reported slightly higher mean values for Attention (4.17 compared to 4.08 in our Physics cohort), the AI-integrated Llama–ARCS framework achieved higher scores across the other three dimensions: Relevance (4.67 vs. 4.08), Confidence (4.33 vs. 4.03), and Satisfaction (4.55 vs. 4.24). These improvements suggest that real-time AI-driven personalization enhances learners' perceived relevance and confidence beyond what static VR systems can offer. However, this comparison remains descriptive rather than inferential, as differences in participant populations and study contexts may influence direct comparability.

Likewise, technical frameworks such as LatticeWorld [22] used Llama 2 for efficient procedural generation but lacked an empirical assessment of student motivation. The Llama–ARCS framework addresses these dual limitations by combining real-time AI adaptivity with rigorous empirical validation based on Keller's ARCS model, achieving consistently high mean scores for Relevance (4.69) and Satisfaction (4.65) across both technical and non-technical student groups. Table 3 presents a structured comparison with existing frameworks, emphasizing the unique combination of AI adaptivity, cache optimization, and motivational assessment achieved in the present study.

Table 3. Comparison with state-of-the-art frameworks

Study	AI Integration	Cache Optimization	Empirical Validation (Motivation)
El Hajji et al. [7]	Yes (LLM-based NPCs)	No	None (Technical only)
Portuguez-Castro and Garduño [26]	No (Static VR)	N/A	Yes (ARCS Model)
Duan et al. [22]	Yes (Llama 2)	No	None
Proposed Framework	Yes (Llama 2)	Yes (Cache Layer)	Yes (ARCS Model)

6. Conclusions

This study successfully developed and evaluated an AI-VR system designed to enhance personalized learning experiences in higher education, addressing critical gaps in both pedagogy and system performance. The results demonstrate that the system consistently supported learner motivation across both student groups. Although the internal consistency for the Confidence dimension reflected the expected variability associated with first-time exposure to VR hardware, the overall motivational impact remained statistically consistent across different academic disciplines. This indicates that the system's educational effectiveness is both robust and transferable, regardless of learners' prior technical background.

In addition to its pedagogical contribution, the study validated a key technical enhancement by implementing a cache-layer optimization. This mechanism was crucial in maintaining a stable and responsive immersive environment. By significantly reducing interaction latency and eliminating system crashes, the architecture ensured that AI-driven adaptive feedback was delivered seamlessly—preserving the high level of immersion essential for effective experiential learning.

Overall, this research reinforces the transformative potential of AI–VR integration in advancing personalized, data-driven, and immersive education. By uniting technological innovation with established motivational theory, the study provides a solid foundation for the development of intelligent classroom systems in higher education. Future research will build on this foundation by fine-tuning the Llama model to align with local curricula and by exploring more advanced caching and hybrid AI strategies to enhance further the educational relevance and technical scalability of the system.

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