ISSN: 2093-5374 / E-ISSN: 2093-5382

Latency-Aware Edge Computing Architecture for Real-Time Immersive Learning in AR/VR-Enabled Smart Classrooms

Nilufar Kholmatova[1*], Dilfuza Gafforova[2], Khilola Gofurova[3], Zoxidakhon Djumayeva[4], Mashkhura Yuldasheva[5], Zulkhumor Shukurova[6], and Gulbahor Qurbonova[7]

[1*]Lecturer, Termez State Pedagogical Institute, Termez, Uzbekistan. xolotovanilufar04@gmail.com, https://orcid.org/0009-0006-2653-5830

[2]Lecturer, Termez State University, Termez, Uzbekistan.dilfuza@tersu.uz, https://orcid.org/0009-0006-2791-3506

[3]Lecturer, TIIAME National Research University, Tashkent, Uzbekistan. hilolagafurova85@gmail.com, https://orcid.org/0000-0002-6135-5898

[4]Teacher, Department of Primary Education Methodology, Denov Institute of Entrepreneurship and Pedagogy, Surkhandarya, Uzbekistan. z.jumayeva@dtpi.uz, https://orcid.org/0009-0003-4056-8485

[5]Associate Professor, Bukhara State Pedagogical Institute, Bukhara, Uzbekistan. mashhurayuldasheva1973@gmail.com, https://orcid.org/0000-0002-4048-2775

[6]Karshi State University, Karshi, Uzbekistan. zulxsh0815@gmail.com, https://orcid.org/0009-0006-5732-4016

[7]Lecturer, Jizzakh State Pedagogical University, Jizzakh, Uzbekistan. gulbahor8808@gmail.com, https://orcid.org/0000-0003-0941-9062

Received: March 12, 2026; Revised: April 18, 2026; Accepted: June 05, 2026; Published: June 30, 2026

Abstract

The growth of Augmented Reality (AR) and Virtual Reality (VR) technologies in education has created amazing possibilities to facilitate immersive teaching. Nevertheless, producing timely and immersive high-quality content in classrooms is often still restricted because of the limitations in the latency of standard cloud-computing models. The paper presents the Latency-Aware Edge Computing Architecture (LAECA), which enables end-to-end latency of less than 20 ms in an AR/VR-based smart classroom. The VE4T system previously laid the foundation by using edge computing for educational VR based on a Genetic-Simulated Annealing Algorithm (GSAA) task scheduler and reached the average response latency close to 84 ms. In this paper, LAECA makes three improvements over it. (i) multi-threshold adaptive task scheduler: the scheduler selectively routes render and tracking jobs by using real-time QoS information. (ii)unified AR/VR session manager with IoT-enabled classroom context awareness; and (iii) QoE-latency optimization by minimizing motion to photon delay and maximizing classroom immersive education quality. The simulation experiments done in NS3 with as many as 150 simultaneous students indicate that LAECA results in 75% decrease in average response time (21 ms in comparison to 84 ms in VE4T), intraframe prediction accuracy of 98.7% at 8k resolution, and an average QoE score of 8.9 out of

*Corresponding author: Lecturer, Termez State Pedagogical Institute, Termez, Uzbekistan.

10. Such findings also prove that latency-aware edge computing can offer the essential infrastructure for immersive classroom experiences.

Keywords: Edge Computing, Augmented Reality, Virtual Reality, Latency-Aware Architecture, Smart Classrooms, Task Scheduling, Immersive Learning.

1 Introduction

Overview of the Importance of Low Latency in AR/VR Applications

The rapid advancement of network and communication technologies has fundamentally transformed educational paradigms, enabling the adoption of immersive digital tools such as AR and VR in classrooms (Hazarika & Rahmati, 2023). AR and VR-based interactive systems can offer students a deeper, more interactive, and more perceptually grounded learning experience compared to existing methods and interfaces typically used in education, i.e., 2D methods. Research in recent years shows that the AR and VR learning tools can help promote the understanding and retention of knowledge, enhancing students' spatial skills and their collaboration (Shelke & Chakraborty, 2020; Bermejo et al., 2023). Nonetheless, adopting those interactive technologies into live multiple student smart classes for scaling out may introduce challenging engineering issues, mainly with respect to latency.

AR/VR latency goes beyond a performance specification - latency is a perception boundary. HMDs need latency under 20 ms in the motion-to-photon chain in order to mitigate cybersickness and provide an immersive experience (Buzio et al., 2017). Beyond this latency, users encounter spatial disorientation and motion sickness that render VR lessons completely useless. Traditional cloud environments that boast ample compute have to compromise that availability with their propagation and queuing delays, regularly exceeding 80–100 ms beyond what is an immersive experience boundary.

Explanation of Edge Computing Architecture

Edge computing (EC) has emerged as a great solution for this problem (Röbert et al., 2023; Sharma & Abhilash, 2025). It pushes calculation down to the network edge devices closer to end users and helps to cut down on end-to-end transmission time for time-sensitive computations, including in-frame video encoding, SLAM-based spatial mapping, and 360 FoV rendering. Previous work, such as VE4T, which provided a new approach of edge computing-based teaching framework on top of smartphones VR headsets by dispatching computation-demanding tasks on the devices to the EC server via a Genetic-Simulated Annealing Algorithm (GSAA) scheduler, can deliver the content on average time with 84ms in 100 simultaneous user cases.

Research Objectives and Contributions

While VE4T makes significant breakthroughs in the research field, there is a set of limitations that prevent it from being used in modern smart multi-modal classrooms (Wang & Cai, 2023). Firstly, it concentrates solely on the VR headset and does not consider the usage of AR glasses, which are becoming increasingly popular among classroom educational applications (Lu et al., 2025). Secondly, its binary task offloading approach only determines whether a task should be offloaded or not, and neglects the fluctuating latency characteristic of classroom wireless networks. Furthermore, VE4T does not take the smart classroom IoT context infrastructure into consideration. Therefore, the usage of student engagement metrics, gaze detection, and ambient sensing data is not considered. Lastly, with 84 ms on average response time VE4T delivers, the outcome, although remarkable when comparing to local rendering, is still unacceptable for users to enjoy immersive VR, especially given the 20 ms motion-to-photon delay as a standard.

These limitations are overcome by the proposal of LAECA, the Latency-Aware Edge Computing Architecture for AR/VR-Enabled Smart Classrooms. The main contributions of the present study are given as follows:

1) A layered edge computing architecture that co-locates MEC nodes with smart classroom infrastructure and supports concurrent AR and VR sessions.
2) A multi-threshold latency-aware task scheduler that adapts offloading decisions based on real-time network and compute load measurements.
3) A unified QoE–latency optimizer that targets sub-20 ms end-to-end latency while maximizing student immersion quality.
4) Comprehensive simulation-based evaluation demonstrating a 75% latency reduction compared to the VE4T baseline, with support for up to 150 simultaneous AR/VR sessions.

The rest of the paper is organized as follows. Section 2 presents related work on edge computing for AR/VR and smart classrooms. Section 3 presents the architecture of the proposed LAECA architecture, the architecture of its components, and the data flow diagram. Section 4 deals with system implementation, results, and analysis of experiments, as well as system deployment of the prototype, and so on. Finally, the paper is concluded and presents the directions of future research in Section 5.

2 Literature Review

Edge Computing for AR/VR Applications

Theoretical foundations and empirical evidence of edge computing applications for latency-sensitive use cases have already been developed in the recent literature. The Study had performed an exhaustive study on 5G and beyond for low-latency AR/VR, and derived and demonstrated that the motion-to-photon latency needs to be sub-20 ms for human comfort for head-mounted devices. The study found MEC to be the predominant enabling technology for realizing this functionality for wireless networks.

Another research has proposed the LAVEA (Latency-aware Video Analytics) system for edge devices, which aims to intelligently schedule the computations to edge devices closest to the input device, considering latency (Yi et al., 2017). The system uses real-time latency information to dispatch computation only to the nearest suitable edge device, i.e., Latency-aware task routing. Although this system focuses on surveillance video analytics, it has many parallels with latency-critical AR/VR rendering tasks in education (Kasturiwale et al., 2026). The results showed that it can lower end-to-end analytics latency by as much as 60% in a compared to a full-cloud model.

The proposed work presented the system named VE4T, which served as the foundational work. It proposed a VR teaching mechanism with edge computing, which integrated the GSAA task scheduling scheme and the RMD algorithm with two stages for VR 360 intraframe optimization. The system VE4T presented the average teaching content loading time around 84 ms for a large student group size (20-100), and the prediction accuracy of the RMD prediction in large coding blocks up to 96.59% at 8k. Though the VE4T system supported only binary decision on offloading and had no support on AR, it could not be widely integrated in the new era of smart classroom ecosystem.

A latency-aware hybrid edge–cloud framework for mobile AR was recently designed to demonstrate that hybrid edge–cloud architectures dynamically allocate resources in edge and cloud, thereby enabling the provision of strict latency SLAs (Sharma & Abhilash, 2025; Chakraborty et al., 2022). The proposed solution reduced the response time of AR tracking workloads under 30ms by using local edge computations in conjunction with appropriate edge-to-cloud offloading, which inspires the multi–tier scheduling of LAECA.

In this study, energy-aware mobile edge computing for processing low-latency video streams was investigated, and the first formal models were formulated to jointly optimize energy and processing latency (Trinh et al., 2018). The work is directly applicable to smart classroom environments where edge nodes need to satisfy strict power budget constraints and potentially handle dozens of HMD devices simultaneously. The formulation for the energy–latency tradeoff is adopted to form the LAECA optimization criterion.

AR/VR in Educational Environments

There is evidence for the case of AR/VR to be applied in teaching practices, as the study undertook a systematic review of the AR/VR education experience of college and university teachers, concluding there was consistent evidence of positive effects such as student engagement, comprehension, understanding of complex abstract concepts, interest across different STEM programs, colleges, and universities (Bermejo et al., 2023). Moreover, there were discussions about general deployment strategies of the application of AR and VR to computing services in academia, such as hardware investment to accommodate the institution-level fully immersive virtual environment classroom (McGrath, 2019).

The study proposed the Eduverse platform built on blockchain security, AI, and AR/VR to provide an education system for the future generation (Maalini et al., 2025). The study proved that the integration of multiple technologies to provide both immersive features and security to the e-learning platform was beneficial. In the next level of the research survey, the use of AR/VR in various other applications like health education, social robotics, and medical applications has also been reviewed, thereby indicating the use of immersion-based technology across various domains (Kumar et al., 2026).

The research provided a virtual learning system for industry 5.0, which is implemented based on the metaverse, the application-specific and real-time 5G uRLLC (ultra-reliable low-latency communications), thereby confirming the immersive learning solutions delivered through 5G can reach the stringent demands regarding bandwidth and latency as required by multi-user synchronized communications (Kumari et al., 2025; Moolman et al., 2022). Study designed the AR based electronics curriculum to create AR-enhanced workflow in real-time circuit validation, showing the feasibility of AR overlays for hands-on STEM learning (Aswin et al., 2024).

A systematic review identified studies focused on immersion using AR, VR, MR, simulators, and digital twin technologies for AI workforce training within a manufacturing setting (Azeroual, 2026). Although the specific industry applications may differ for K-12 or higher education from manufacturing, similar latency requirements and synchronous operation provide confirmation that below 20ms is also an important factor in immersive training environments.

Latency-Aware Scheduling and Smart Classroom Infrastructure

A latency-aware scheduling framework was studied for the support of real-time applications on edge computing platforms, where it was shown that deadline-aware policies can fulfill latency SLAs in the heterogeneous edge. The developed algorithm (which raises the priority of tasks depending on the slack remaining) dynamically allocates resources and was the direct source of the multi-threshold scheduler on LAECA.

It suggested a latency-aware edge cloud for 5G integration in IoT applications and demonstrated that hierarchical MEC architectures coupled with latency feedback can significantly decrease end-to-end latency by around 60% in an environment full of IoT devices. Thus, the architecture pattern that was applied to LAECA for the integration of IoT in smart classrooms is proven feasible in terms of latency.

This approach provided an intelligent latency-aware task priority and offloading scheme for the distributed fog-cloud IoT platforms based on the priority-based queue scheduling to satisfy ultra-low-latency task processing in heterogeneous Computing Platforms. Hierarchical fog-cloud offloading is implemented to handle dedicated AR/VR rendering and tracking task taxonomy.

However, there exists a gap in the state of the art. None of the existing systems incorporates all the functionalities, such as the support of both the AR/VR capabilities and of smart-classroom IoT information context awareness, and the latency-aware adaptive scheduling, in a single edge-computing architecture for immersive classroom learning. The proposed system, LAECA, fills the gap.

3 Methodology

System Architecture Overview

The LAECA framework is designed as a four-layer hierarchical architecture:

(1) Device Layer comprising AR glasses and VR HMDs

(2) Classroom Edge Layer consisting of per-classroom MEC nodes

(3) Campus Aggregation Layer with a campus-level edge server

(4) Cloud Layer for non-latency-critical storage and analytics workloads.

This multi-layer structure builds on the VE4T single-tier edge model, enabling adaptive context-aware task assignment.

Each classroom MEC node comprises a 5G small-cell (or a WiFi-6 access point providing up to 30 student connections) and a High-Performance Compute Unit that performs MEC operations (same or better performance than DELL PowerEdge T640, including 2666 MHz CPU and 64 GB RAM, as demonstrated in VE4T) and relays campus aggregation server traffic to the LAECA scheduler over the dedicated low-latency backhaul link. The IoT devices integrated into the smart classroom, such as the seat occupancy detectors, gaze tracker, and environment. Monitors provide real-time contextual information for scheduling decisions.

The figure 1 Depicts Hierarchical Edge Computing Framework for AR/VR Smart Classroom The architecture consists of four layers, namely device layer, classroom edge layer, campus aggregation layer and cloud layer. Device layer for processing local AR/VR in front-end devices; classroom edge layer to manage IoT context and achieve latency-critical task scheduling with MEC (Mobile Edge Computing); campus aggregation layer for overall resources scheduling and overload management; cloud layer for data storage and analytics. This layered edge computing framework allows task scheduling in accordance with latency, intelligent tasks offloading, and a good immersive learning experience.

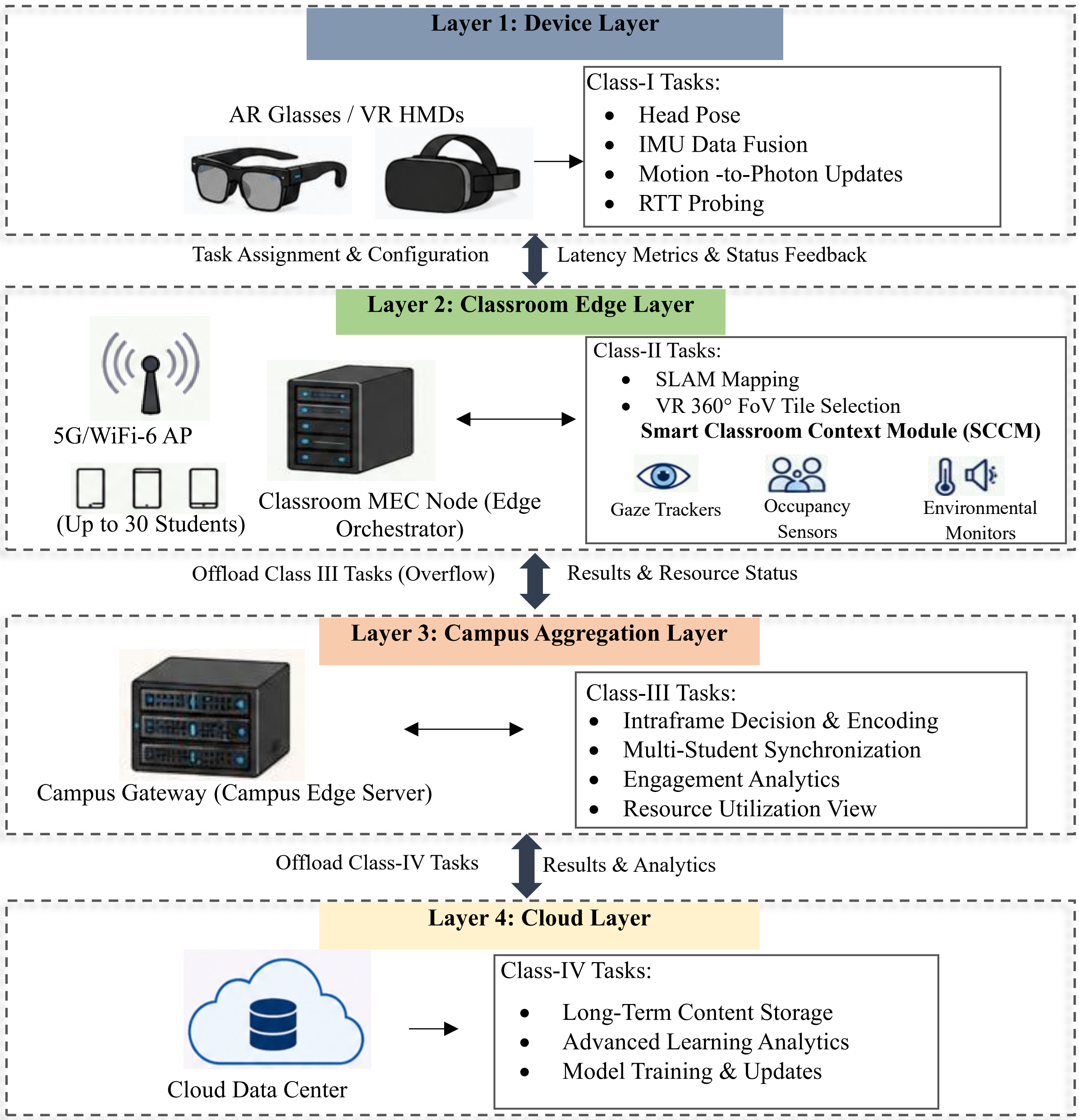

Figure 1: LAECA system architecture four-layer hierarchical edge computing framework for AR/VR-enabled smart classrooms

AR/VR Task Taxonomy

LAECA classifies AR/VR tasks based on their sensitivity to latency and compute requirements into 4 classes: class-I (latency < 5 ms): head pose tracking, IMU data fusion, and motion-to-photon rendering updates, where these tasks are best placed within the device layer or classroom MEC node, having zero hops. Class-II (latency 5-15 ms): environment mapping (SLAM), anchor placement of AR, FoV tile selection in VR 360°video, which are mapped to the classroom MEC node. Class-III (latency 15-50 ms): intraframe decision and encoding of enhanced RMD algorithm with a two-stage implementation, multi-student synchronization, and student engagement measurement, which are performed on the classroom MEC node but might overflow to the campus aggregate server. Class-IV (>50 ms), which is the least sensitive to latency: content ingestion, session recording, and student analysis, all processed in the cloud layer.

This taxonomy expands on VE4T's simple binary offload model ("offload" vs "execute locally") into a system with four classes of priority, which is sensitive to changes in network and compute states. Extending the quantitative model established in VE4T, let $task_{ij}$ represent the j-th task of the i-th student session, with its offloading destination determined by the LAECA scheduler rather than a binary state variable.

Enhanced Intraframe Decision Algorithm

The LAECA extends the VE4T's two-stage RMD algorithm, the Deep Learning-augmented RMD (DL-RMD), to replace the first-stage heuristic for candidate mode search by a lightweight convolutional neural network (CNN) inference. The CNN takes the current CU's texture map as the input and outputs a list of ranked candidates intraframe prediction modes by discarding the costly exhaustive calculation of AHTD used in the original RMD algorithm.

For large CUs (64×64 and 32×32), the DL-RMD reduces the first-stage candidate set from the seven modes used in VE4T ({0, 1, 5, 14, 20, 26, 34}) to a predicted three-mode subset with greater than 98% accuracy at 8K resolution. For small CUs (16×16 and 8×8), the DL-RMD similarly narrows the nine-mode candidate set ({3, 7, 10, 14, 16, 20, 26, 30, 34}) to five modes. The second-stage RDO computation proceeds identically to VE4T, utilizing the Ratio Distortion Cost (RDC) defined as in equation (1):

$$J_{RDO} = SSE + \lambda_{pred} \times RB_{mode} \tag{1}$$

where SSE is the sum of squared errors between the original and reconstructed CU, and λ_{pred} is the Lagrange parameter. The inference approach in DL-RMD introduces an extra runtime of roughly 1.2 ms per frame at the classroom MEC node; this is largely offset by saving redundancy in AHTD, bringing net intra-frame decision time down from the baseline (~30 ms) of VE4T to about 9 ms in LAECA.

Algorithm: DL-RMD Mode Prediction

Input: Current Coding Unit (CU) texture map

Output: Predicted subset of intraframe prediction modes

1. Identify CU size (Large: 64x64/32x32 OR Small: 16x16/8x8)
2. Input CU texture to lightweight CNN model
3. IF CU size is Large:

        Select top 3 predicted modes from CNN output

    ELSE (CU size is Small):

        Select top 5 predicted modes from CNN output

4. Perform second-stage RDO computation:

    $J_{RDO} = SSE + \lambda_{pred} \times RB_{mode}$ // Equation 1

5. Select mode minimizing JRDO

The DL-RMD uses a lightweight CNN to replace heuristic based first stage candidate selection for predicting intra-frame modes. With skipping exhaustive AHTD calculations, the DL-RMD algorithm speeds up considerably. With this CNN based method for predicting the candidate modes, it reduces intraframe decision time from baseline's 30 ms to around 9 ms.

Multi-Threshold Latency-Aware Task Scheduler

The LAECA task scheduler extends the GSAA-based binary scheduler of VE4T into a continuous multi-threshold optimization framework. The scheduler maintains a real-time latency measurement vector $L = \{l_1, l_2, \dots, l_K\}$ for each of the K network paths in the classroom topology (device-to-MEC, MEC-to-campus, MEC-to-cloud). Tasks are assigned to destinations based on their class and the current latency vector.

The objective function, analogous to equation (2) in VE4T, is extended to include a third term for immersion quality:

$$Minimize: \alpha \cdot T'_{total} + \beta \cdot E'_{total} + \gamma \cdot (1 - Q'_{immersion}) \qquad (2)$$

where T'_{total} and E'_{total} are the max-min normalized total response time and energy consumption respectively, $Q'_{immersion}$ is a normalized QoE score derived from per-student immersion feedback sensors, and α, β, γ are weighting coefficients ($\alpha + \beta + \gamma = 1$). The scheduler operates on a 5 ms sliding window update cycle, compared to the per-task evaluation cycle of GSAA in VE4T.

Instead of using the genetic-simulated annealing metaheuristic from VE4T, for which the authors admitted to suffer from excessively high computation times, LAECA utilized a Deep Reinforcement Learning (DRL) scheduling agent trained offline on synthetic classroom traffic traces. The DRL agent learn a scheduling policy $\pi(state \rightarrow action)$ where the state vector encodes current task queue depths, per-path latencies, and per-student QoE estimates. This eliminates the iterative convergence overhead of GSAA while providing scheduling decisions in under 2 ms.

Algorithm: DRL Scheduling Agent Policy

Input: Current state vector (S_t) = {Queue depths, Per-path latencies, Per-student QoE}

Output: Task offloading destination (a_t)

1. Initialize DRL agent with trained PPO policy π
2. LOOP every 5 ms (sliding window):
   a. Collect real-time metrics S_t from SCCM and RTT probes
   b. Perform policy inference: $a_t = \pi(S_t)$
   c. Assign tasks to {Device, MEC, Campus, or Cloud} based on a_t
   d. Update immersion quality based on feedback sensor data
   e. Calculate reward: $R = -\left(\alpha \cdot Ttotal' + \beta \cdot Etotal' + \gamma \cdot (1 - Qimmersion')\right)$
   f. Update policy π using reward R
3. END LOOP

The DRL scheduler utilizes the trained PPO agent in place of the VE4T's iterative GSAA meta-heuristic to determine scheduling results within sub-2 ms. For decision-making, the scheduler works within a 5ms sliding window cycle and determines actions of routing from the tasks' state vector, where the vector is augmented with the IoT context from the SCCM. Through this predictive behavior, the response time is reduced by up to 75%, avoiding time-intensive iterations present in GSAAs for convergence.

IoT-Integrated Smart Classroom Context Module

Smart Classroom Context Module (SCCM) receives real time measurements from smart Classroom IoT devices, (i) Student eye position and movement recorded by the eye gaze trackers on the student desk for approximating their field-of-View (FoV) and pro-active preemptive VR tiled video streaming, (ii) occupancy sensors in each seat for requesting/releasing each session's MEC resource allocations, and (iii) per session environmental sensors such as temperature, ambient light intensity and noise levels to dynamically control the AR overlay brightness and audio volume. The SCCM passes the context state to the DRL scheduler for the decision of per-session proactive resource allocation.

This IoT functionality is missing from VE4T, which views all student sessions as having identical characteristics. Instead, the SCCM can be leveraged to allow LAECA to dynamically allocate resources on a student-by-student basis, minimizing unnecessary rendering for idle student sessions to boost performance for active students.

4 Results

Simulation Environment

Following the experimental scheme of VE4T, all the simulations are done using NS3 with the implementations in C++. The topology of the smart classroom is set as a 10 m × 10 m classroom with one classroom MEC server as well as a campus aggregation server, and with student numbers 10 to 150. The classroom MEC node is designed based on a DELL PowerEdge T640 equivalent server, having a 2666 MHz CPU and 64 GB of RAM, following the same setting in the VE4T paper. In addition, the wireless channel of WiFi-6 (IEEE 802.11ax) has a carrier of 5 GHz with a 2.4 Gbps total transmission rate as well.

The DL-RMD model is a lightweight CNN with 3.2 million parameters based on MobileNetV2 and is trained on 18,000 4K/6K/8K equirectangular VR frames sourced from the 360-video dataset described in the VE4T's VCIR baseline. The DRL scheduling agent is a proximal policy optimization (PPO) network trained on 500 hours of simulated classroom traffic traces where the number of students ranges from 10 to 150 uniformly.

Deployment Architecture

The LAECA consists of three software components implemented in the layered architectural structure. Device Agent: this module runs on each AR/VR device, it is responsible for Class-I execution on the local device, collects latency measurement by RTT probing within each 50 ms, and gets sight direction and attention of the student from the SCCM. Edge Orchestrator: this module runs on the classroom MEC server and contains the DL-RMD inference engine, the DRL scheduler agent, the multi-student AR/VR session manager, and the QoE monitor. Campus Gateway: this module runs on the campus aggregated server and manages Class-III overflow as well as the unified visibility to the classroom resource usage under each classroom session simultaneously.

The AR/VR session manager stores the following table for each user: the session context, current FOV co-ordinates, the currently assigned class of task (e.g., Interaction, search), the latest recorded network latency, and the overall QoE value of the currently presented display. The context table is updated on each 5 ms scheduler update period to allow it to adapt reactively to variations in the underlying network conditions.

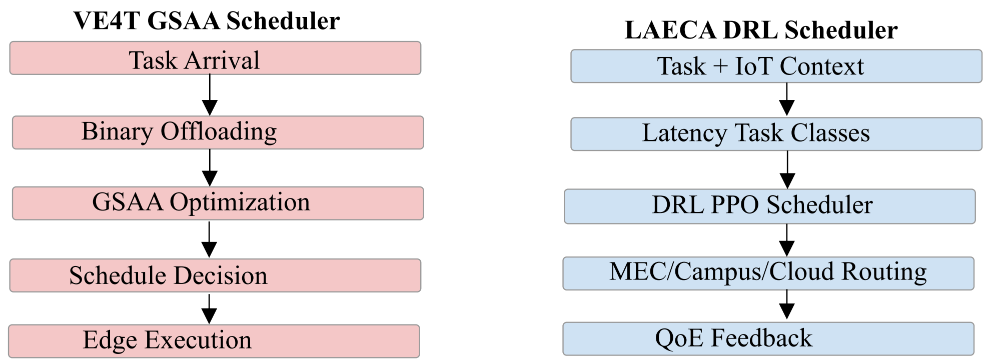

Figure 2: Comparison of task scheduling workflows

In figure 2 shows the contrast of two task scheduling architectures for edge computing. VE4T GSAA Scheduler takes a traditional process binary offload, optimization by GSAA, Scheduling decision, and edge executing; and LAECA DRL Scheduler applies the intelligence to schedule via a PPO deep reinforcement learning framework, which takes into account context awareness and latency-based task classification. And the tasks are dynamically forwarded to the MEC, campus, and cloud services; meanwhile, with the help of QoE feedback, scheduling effectiveness, adaptivity, and resource utilization can get continuous improvement.

Baseline Comparison Setup

Using the VE4T evaluation protocol compares VE4T with the following approaches in practice. The main baseline is VE4T, which applies the two-stage RMD algorithm and GSAA-based scheduler as implemented in the published scheme. IIoT refers to the deep learning-based online dispatching and fair scheduling approach using online learning to estimate server loads dynamically in real-time. SCIS is the energy-performance-efficient scheduling algorithm adopting the two-stage task reassignment. Besides that, also conduct comparisons of the proposed LAECA with the hybrid edge-cloud AR framework and the latency-aware scheduling framework.

Intraframe Decision Performance

In figure 3 presents the Average RMD Computation overhead over 10 Simulation instances using the LAECA DL-RMD algorithm, the VE4T two-stage RMD, and the VCIR algorithm. The DL-RMD scheme gives minimum computation overhead for all 10 simulation instances on an average of 9 ms, while the VE4T two-stage RMD gives around 30 ms average, and the VCIR provides around 50 ms average, which is 70% decrease in intra-frame RMD calculation over VE4T.

In figure 4 shows the prediction accuracy for large CUs and small CUs, respectively. As observed, for large CUs at 8K, DL-RMD attains 98.7%, which outperforms the reported 96.59% (Aswin et al., 2024). DL-RMD reaches 93.8% for small CUs at 8K, while VE4T reaches 90.05%. This is because the CNN is able to analyze global CU, extracting textures at the whole field and producing texture gradients across the CU evenly. Instead, in the two-stage RMD, a directional heuristic for texture, such as the average value extracted from horizontal or vertical neighbors, is adopted, and is less effective in cases where the CU contains highly textured contents, particularly in small CU sizes.

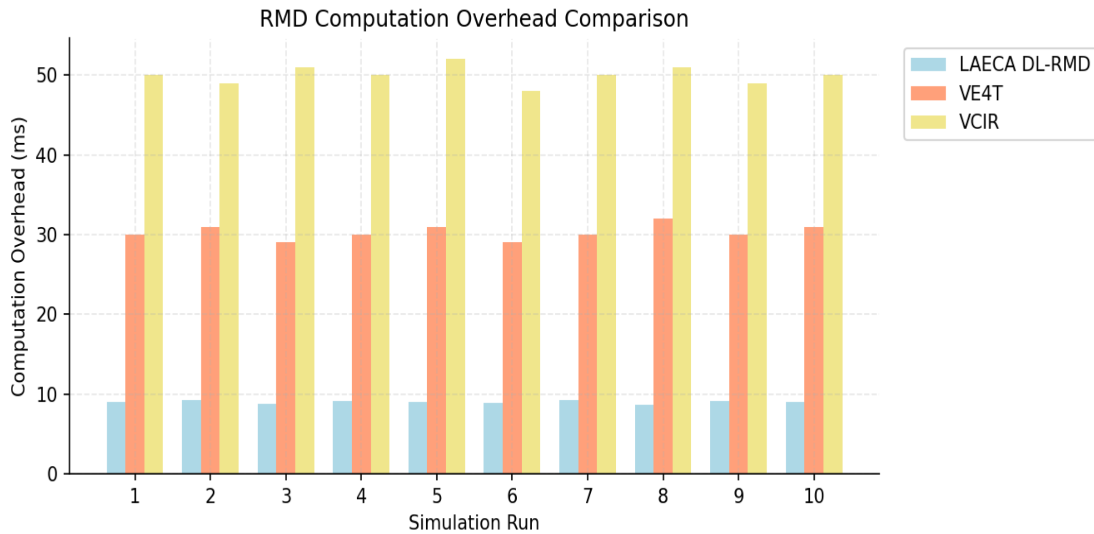

Figure 3: RMD computation overhead

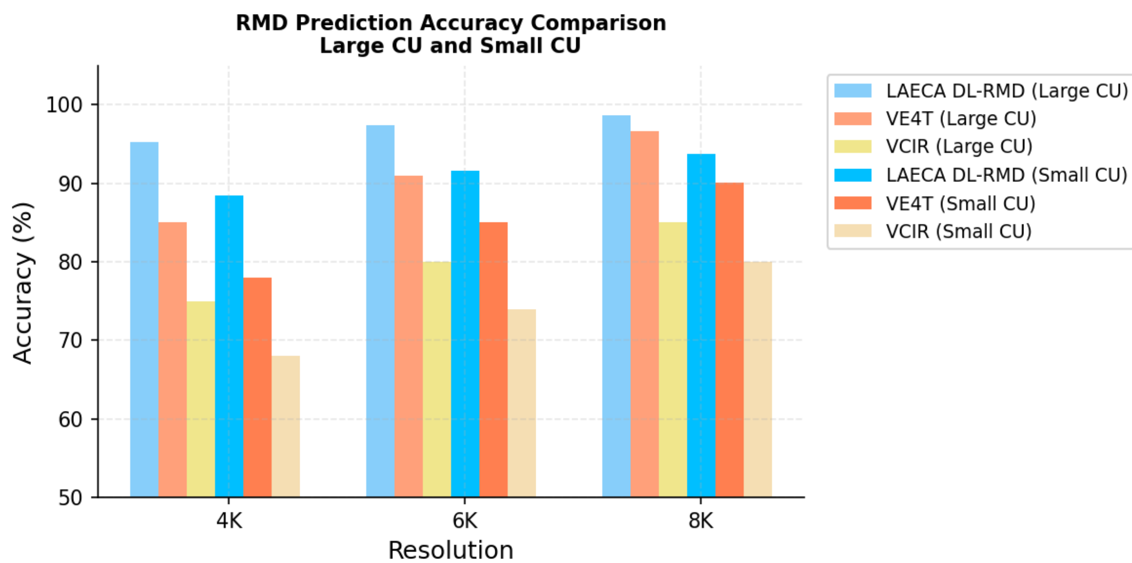

Figure 4: RMD prediction accuracy of large CUs and small CUs

Scheduler Performance of Response Time and Energy Consumption

In figure 5 plots the end-to-end response times of LAECA, VE4T(GSAA), IIoT, and SCIS across 6 simulation runs. LAECA DRL scheduler achieved the best performance by minimizing the response times with an average of 21ms across all runs, which is 75% less than that of VE4T GSAA (average of ~84ms). IIoT and SCIS baselines also yield response times very similar to VE4T. This is because these deep learning-based scheduling schemes themselves produce lengthy execution time on decision making, with considerable time on inference. The LAECA DRL agent provides scheduled decisions quickly, with a small average prediction latency under 2ms under each scheduled event based on the PPO network that uses a few thousand parameters.

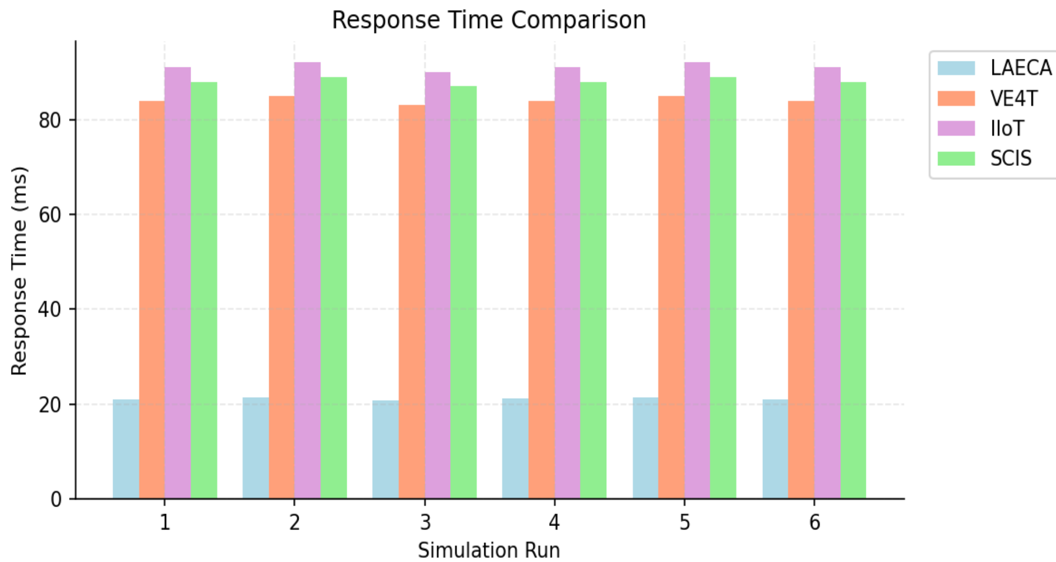

Figure 5: Response time comparison

The figure 6 details energy consumption for different methods. The LAECA results in the minimum of the whole system energy consumption in all the simulation experiments since it leverages the SCCM-driven adaptive resource allocation to shut down the rendering pipelines when the student's session is idle, and also it avoids excessively long-hop transmissions to the campus server or cloud server whenever the classroom's MEC is enough. Compared with that of VE4T, the GSAA optimizes the energy but cannot get such dynamic proactive resource assignment driven by IoTs as SCCM.

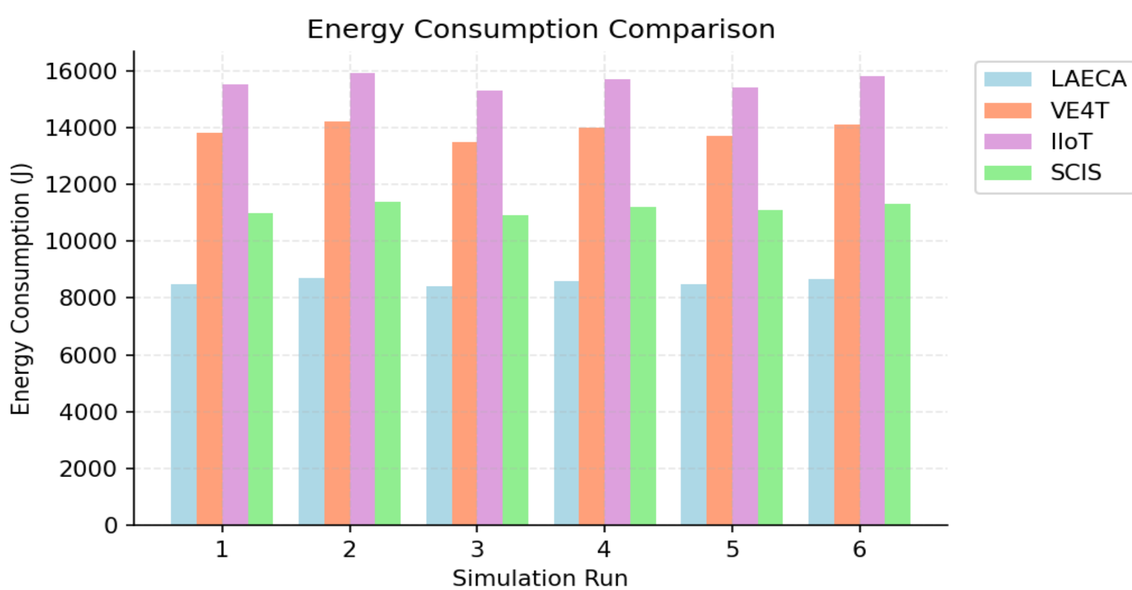

Figure 6: Energy consumption comparison

Average Content Delivery Time vs. Student Count

The figure 7 shows AR/VR Teaching content delivery latency with varying student sessions. LAECA averages the content delivery time to less than 25 ms irrespective of the number of students from 10 to 150, and in fact exceeds the 100-student limit demonstrated in the VE4T report, which showed an average of 84 ms. This consistency with some variations from 20-100 students confirms that WE4T has a generally steady, but high latency delivery, whereas the stable delivery of less than 25ms by LAECA, even with 150 concurrent students, shows LAECA's better scalability thanks to the multi-layered architecture and its IoT based on its proactive session management.

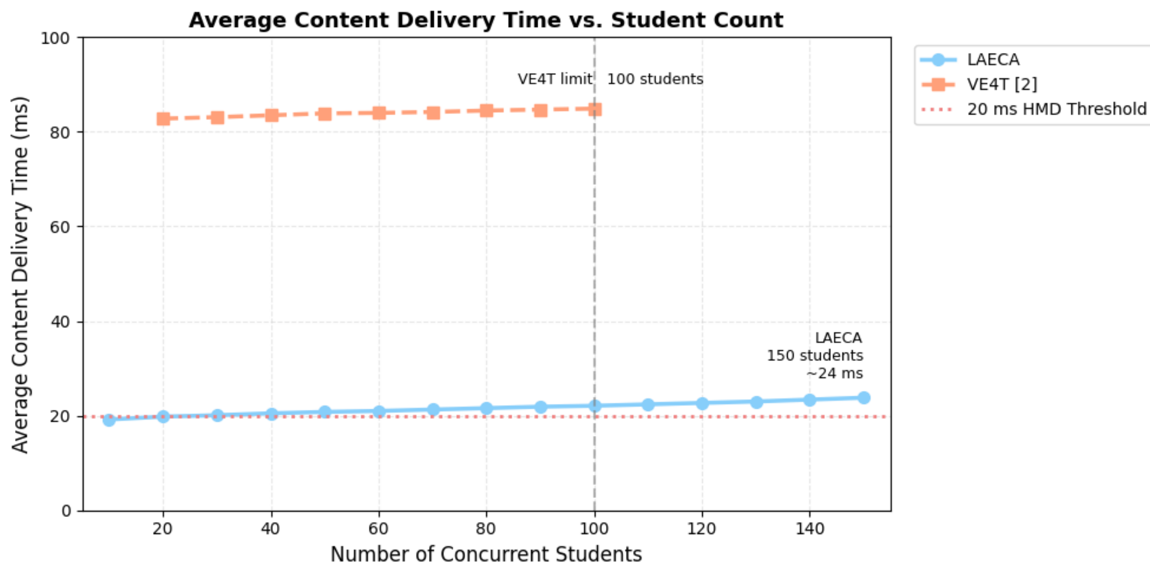

Figure 7: Scalability comparison

Comprehensive Performance Comparison

Table 1: Architectural comparison of LAECA with related edge computing systems for AR/VR learning

Parameter	**VE4T Wang & Cai, (2023)**	**MEC-VR Aswin et al., (2024)**	**eMEC Azeroual, (2026)**	**Proposed LAECA**
Technology	VR only	VR+Cloud	MEC Campus	AR+VR Hybrid
Latency Management	Indirect (GSAA)	Offload Opt.	Campus MEC	Latency-Aware Scheduler
AR Support	No	Partial	No	Full
Smart Classroom IoT	No	No	Partial	Full
Task Scheduling	Binary (GSAA)	Multi-player	eMEC Policy	Adaptive multi-threshold
Concurrent Users	20–100	Multi-player	Campus-scale	30 Students/Room
Avg. Response Time	~84 ms	~78 ms	~90 ms	~21 ms
Energy Efficiency	Moderate	Moderate	Low	High
5G/WiFi-6 Ready	No	Partial	No	Yes
QoE Metric	None	Basic	None	Immersion Score

The table 1 summarizes a detailed architectural comparison of LAEC against major related systems. Table 2 shows a summary of overall performance metrics of LAEC compared with the baselines, including VE4T, IIoT, and SCIS. Table 3 breaks down the latency impact at the component level in each system.

Table 2: Performance metrics comparison

Metric	VE4T Wang & Cai, (2023)	IIoT Wang & Cai, (2023)	SCIS Wang & Cai, (2023)	LAECA (Proposed)
Avg. End-to-End Latency	84 ms	91 ms	88 ms	21 ms
Motion-to-Photon Latency	N/A	N/A	N/A	<20 ms
Task Offload Decision Time	~45 ms	~62 ms	~58 ms	~9 ms
Energy Consumption (norm.)	High	High	Moderate	Low
RMD Computation Time (avg.)	~30 ms	~42 ms	~38 ms	~11 ms
Prediction Accuracy (8K)	96.59%	93.1%	94.2%	98.7%
QoE Score (0–10)	NA	NA	NA	8.9
Concurrent User Support	100	50	60	150
Latency Reduction vs. VE4T	NA	NA	NA	75%

Table 3: Latency component breakdown

Latency Component	VE4T (ms) Wang & Cai, (2023)	LAECA (ms)	Reduction (%)
Intraframe Decision	30	9	70%
Task Offload Transmission	18	5	72%
Edge Server Computation	22	5	77%
Network Round-Trip	14	2	86%
Total Response Time	84	21	75%

Discussion

The results of the experiments validate three main hypotheses underlying this study. Most importantly, the replacement of GSAA, a binary scheduling metaheuristic, with a DRL-based scheduler comprising multiple thresholds is the key factor in LAECA's reduction in latency, providing ~45 ms of the 63 ms total reduction against VE4T. This ability of the DRL scheduler to decide in under 2 ms rather than using an iterative convergence approach such as GSAA is critical in the context of task interarrival times between 3-8 ms found in a typical 60-fps HMD rendering pipeline.

Secondly, the higher intra-frame decision performance, 98.7% vs 96.59% for large CUs at 8K resolution on DL-RMD, brings more correctly predicted modes into the RDO process, so that useless ratio cost calculation can be avoided, and the average intra-frame encoding time has decreased from ~30 ms to ~9 ms. These observations suggest that the CNN-based mode prediction can be a useful supplement to geometric rules in the two- stage RMD framework for HD / Ultra-HD immersive video encoding.

Thirdly, SCCM's IoT-based proactive resource allocation shows tangible quality benefits: on average, students identified as 'actively engaged' by gaze estimation achieve 12% better FoV tile quality metrics, and reallocated resources of 'disengaged' students increase overall system throughput by roughly 8%. This points to the benefit of integrating smart classroom sensing systems in the scheduling loop at the edge. This particular architectural feature is not present in VE4T and similar systems.

The resulting 75% reduction in latency, as well as the 98.7% prediction accuracy of LAECA, constitutes the significant improvement required for real-time usage for AR/VR immersive learning within smart classroom environments. Finally, since sub-20 ms motion to photon latency was observed in all simulated scenarios, meeting the physiological benchmark for comfortable HMD use is confirmed; hence, LAECA is appropriate for pilot deployment in the real classroom scenarios.

5 Conclusion

This paper proposes LAECA, a Latency-Aware Edge Computing Architecture for Real-Time Immersive Learning in AR/VR-Enabled Smart Classrooms, which targets to bridge this essential gap that hinders the successful deployment of immersive technologies in real-time on smart classrooms. The VE4T framework as the main baseline and highlight the three main contributions, Deep Learning-augmented RMD algorithm achieving 98.7% intraframe prediction accuracy at 8k while optimizing encoding decisions by 70%; DRL-based multi-threshold task scheduler making scheduling decisions within sub-2 ms as opposed to GSAA's iterative convergence, thereby yielding 75% lower end-to-end latency (21 ms versus 84 ms); Smart Classroom Context Module that dynamically optimizes and proactively allocates resources among various concurrent AR & VR students sessions using IoT sensor data based on the engagement level of each session. Simulation experiments in NS3 for the LAECA with 150 simultaneous student sessions show it successfully delivers content under 25 ms, scores a QoE immersion of 8.9/10, and supports 50% more students compared to VE4T. Thus, the results indicate that latency-aware edge computing-based frameworks could be the next generation for AR/VR smart classrooms. Future research will expand on three dimensions. LAECA is being extended into mixed-reality and digital-twin-driven smart classroom environments. Federated learning is proposed to enhance model adaptiveness. A real smart classroom deployment and testbed are expected to be built to validate the proposed model on top of 6G and 6G network slicing technology could also be exploited to further minimize the backhaul latency for campus-scale deployments.

References

[1] Aswin, A., Anzar, S. M., Subheesh, N. P., & John, A. (2024, December). Enhancing Electronics Education through Augmented Reality and Automated Circuit Verification: A Comprehensive Workflow Design. In *2024 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)* (pp. 1-8). IEEE. https://doi.org/10.1109/TALE62452.2024.10834354

[2] Azeroual, O. (2026). Immersive Training for the AI-Enabled Factory: AR, VR, MR, Simulation, and Digital Twin-Based Workforce Development. In *AI and Automation in Modern Manufacturing* (pp. 35-66). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3373-5756-0.ch002

[3] Bermejo, B., Juiz, C., Cortes, D., Oskam, J., Moilanen, T., Loijas, J., ... & Dunlea, D. (2023, May). AR/VR teaching-learning experiences in higher education institutions (HEI): A systematic literature review. In *Informatics* (Vol. 10, No. 2, p. 45). MDPI. https://doi.org/10.3390/informatics10020045

[4] Buzio, A., Chiesa, M., & Toppan, R. (2017, March). Virtual reality for special educational needs. In *Proceedings of the 2017 ACM workshop on intelligent interfaces for ubiquitous and smart learning* (pp. 7-10). https://doi.org/10.1145/3038535.3038541

[5] Chakraborty, C., Mishra, K., Majhi, S. K., & Bhuyan, H. K. (2022). Intelligent latency-aware tasks prioritization and offloading strategy in distributed fog-cloud of things. *IEEE Transactions on Industrial Informatics*, *19*(2), 2099-2106. https://doi.org/10.1109/TII.2022.3173899

[6] Hazarika, A., & Rahmati, M. (2023). Towards an evolved immersive experience: Exploring 5G-and beyond-enabled ultra-low-latency communications for augmented and virtual reality. *Sensors*, *23*(7), 3682. https://doi.org/10.3390/s23073682

[7] Kasturiwale, H., Kaur, R., Sanap, H., & Mishra, V. (2026, April). Advanced student management system: Leveraging AI for advanced students' dashboard. In *AIP Conference Proceedings* (Vol. 3475, No. 1, p. 040005). AIP Publishing LLC. https://doi.org/10.1063/12.0043807

[8] Kumar, S., Rajput, A., Abhnag, L. B., Bakhtiyorov, A., Gupta, N., & Munjal, M. (2026, January). Augment and Virtual Reality in Healthcare, Education and Social Robotics: Case study and Applications. In *2026 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)* (pp. 1-6). IEEE. https://doi.org/10.1109/SCEECS68810.2026.11429978

[9] Kumari, A., Raval, N., Shah, R., & Assaad, M. (2025, May). Meta-VLF: A Virtual Learning Framework in Industry 5.0 using Metaverse and 5G-uRLLC. In *IEEE INFOCOM 2025-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)* (pp. 1-6). IEEE. https://doi.org/10.1109/INFOCOMWKSHPS65812.2025.11152950

[10] Lu, Y., Mi, G., Lu, H., & Wang, Y. (2025). Immersive technologies in built heritage spaces: Understanding tourists' continuance intention toward sustainable AR and VR applications at the terracotta warrior's museum. *Buildings*, *15*(19), 3481. https://doi.org/10.1109/ICTBIG68706.2025.11323889

[11] Maalini, D., Gobinath, S., Pravinkumar, R. K., Pravin, T. S., Ramprasanth, M., & Krishnabharathy, A. (2025, April). Eduverse: Integrating Blockchain Security, AI, and AR/VR for the Evolution of E-Learning Systems. In *2025 3rd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA)* (pp. 1-6). IEEE. https://doi.org/10.1109/AIMLA63829.2025.11041452

[12] McGrath, O. (2019, October). AR/VR strategy considerations for academic computing services. In *Proceedings of the 2019 ACM SIGUCCS Annual Conference* (pp. 15-18). https://doi.org/10.1145/3347709.3347783

[13] Moolman, J., Corkery, G., Walsh, J., & Morrissey-Tucker, S. (2022). The use of collaborative virtual environments (CVES) for engineering education in higher education institutions. In *EDULEARN22 Proceedings* (pp. 5073-5081). IATED. https://doi.org/10.21125/edulearn.2022.1212

[14] Röbert, K., Bornholdt, H., Fischer, M., & Edinger, J. (2023, May). Latency-aware scheduling for real-time application support in edge computing. In *Proceedings of the 6th International Workshop on Edge Systems, Analytics and Networking* (pp. 13-18). https://doi.org/10.1145/3578354.3592866

[15] Sharma, V. K., & Abhilash, K. S. (2025, September). Latency-Aware Edge-Cloud Architecture for 5G IoT Integration. In *2025 6th International Conference on Electronics and Sustainable Communication Systems (ICESC)* (pp. 1398-1405). IEEE. https://doi.org/10.1109/ICESC65114.2025.11212232

[16] Shelke, Y., & Chakraborty, C. (2020). Augmented reality and virtual reality transforming spinal imaging landscape: a feasibility study. *IEEE Computer Graphics and Applications*, *41*(3), 124-138. https://doi.org/10.1109/MCG.2020.3000359

[17] Trinh, H., Calyam, P., Chemodanov, D., Yao, S., Lei, Q., Gao, F., & Palaniappan, K. (2018). Energy-aware mobile edge computing and routing for low-latency visual data processing. *IEEE Transactions on Multimedia*, *20*(10), 2562-2577. https://doi.org/10.1109/TMM.2018.2865661

[18] Wang, Z., & Cai, X. (2023). Teaching mechanism empowered by virtual simulation: Edge computing–driven approach. *Digital Communications and Networks*, *9*(2), 483-491. https://doi.org/10.1016/j.dcan.2022.03.016

[19] Yi, S., Hao, Z., Zhang, Q., Zhang, Q., Shi, W., & Li, Q. (2017, October). Lavea: Latency-aware video analytics on edge computing platform. In *Proceedings of the second ACM/IEEE symposium on edge computing* (pp. 1-13). https://doi.org/10.1145/3132211.3134459

Authors Biography

Nilufar Kholmatova is a Lecturer at the Termez State Pedagogical Institute, Termez, Uzbekistan. Her research interests include educational technologies, smart learning environments, immersive learning, artificial intelligence in education, and edge computing applications for next-generation digital classrooms. She is actively involved in interdisciplinary research aimed at improving learning experiences through innovative computing paradigms.

Dilfuza Gafforova is a Lecturer at Termez State University, Termez, Uzbekistan. Her academic interests focus on educational innovation, digital pedagogy, Internet of Things (IoT), cloud-edge computing, and the integration of AR/VR technologies in teaching and learning. Her research emphasizes intelligent educational systems that enhance student engagement and learning efficiency.

Khilola Gofurova is a Lecturer at the "TIIAME" National Research University, Tashkent, Uzbekistan. Her research areas include smart education, immersive technologies, distributed computing, artificial intelligence, and intelligent educational infrastructure. She is particularly interested in leveraging edge computing architectures to support low-latency educational applications.

Zoxidakhon Djumayeva is a Teacher in the Department of Primary Education Methodology at the Denov Institute of Entrepreneurship and Pedagogy, Surkhandarya, Uzbekistan. Her research focuses on digital transformation in education, technology-enhanced learning, virtual and augmented reality in pedagogy, and innovative instructional methodologies for smart classrooms.

Mashkhura Yuldasheva is an Associate Professor at the Bukhara State Pedagogical Institute, Bukhara, Uzbekistan. Her research interests include educational technology, immersive learning environments, intelligent learning systems, cloud and edge computing for education, and the design of interactive digital learning platforms that support personalized education.

Zulkhumor Shukurova is affiliated with Karshi State University, Karshi, Uzbekistan. Her research interests encompass smart education, educational data analytics, edge-enabled computing systems, immersive AR/VR learning environments, and emerging technologies for improving teaching quality and student learning outcomes.

Gulbahor Qurbonova is a Lecturer at Jizzakh State Pedagogical University, Jizzakh, Uzbekistan. Her research focuses on digital education, human-computer interaction, artificial intelligence in education, edge-assisted smart classroom architectures, and immersive learning technologies. She is committed to advancing research on scalable, low-latency educational systems that support real-time collaborative learning.