A Hybrid AI-VR Architecture for Real-Time Gamified Second Language Acquisition

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Abstract

This paper presents MundoVR, a hybrid AI-VR architecture designed to address the latency, scalability, and cost challenges of integrating Large Language Models into immersive educational environments. By strategically distributing workloads between lightweight on-device processing and cloud-based services, the proposed architecture is designed to target p99 (99th percentile) latency under 1.5 s—a threshold derived from Virtual Reality (VR) immersion and Human-Computer Interaction (HCI) research—while supporting 10,000 concurrent users at estimated costs below $0.10 per session. We provide formal SysML specifications and Architecture Decision Records, offering a reusable blueprint for scalable, pedagogically adaptive AI-VR systems that align with Second Language Acquisition (SLA) principles.

Keywords

Virtual Reality, Large Language Models, Software Architecture, Second Language Acquisition, Microservices, Edge Computing, SysML

1 Introduction

1.1 Motivation and Context

Second Language Acquisition (SLA) research consistently demonstrates that authentic conversational practice is crucial for developing fluency [12]. However, traditional Computer-Assisted Language Learning (CALL) systems fail to provide the spontaneous, contextually rich interactions necessary for developing conversational competence. Meanwhile, recent breakthroughs in Large Language Models (LLMs) and automatic speech recognition have created unprecedented opportunities for intelligent, adaptive dialogue systems. Virtual Reality (VR) technology offers unique affordances for language learning: presence, embodiment, and contextual learning. Studies show VR environments improve vocabulary retention by 35–50% compared to traditional methods [21], while reducing learner anxiety through safe, judgment-free practice spaces [2]. The convergence of these technologies creates the possibility of realistic conversational practice systems. However, integrating them poses significant software engineering challenges: real-time artificial intelligence (AI) inference must maintain VR immersion, handle complex natural language understanding within 1.5 seconds, scale to thousands of concurrent users, and remain cost-effective.

1.2 Problem Statement

Current AI-VR language learning systems face three critical limitations. First, cloud-based LLMs introduce 2–5 second delays, breaking VR immersion, while on-device models lack the contextual reasoning for pedagogically sound conversations. Second, Graphics Processing Unit (GPU)-intensive AI processing creates cost barriers, limiting accessibility and deployment scale. Third, generic LLMs generate grammatically correct but pedagogically inappropriate responses, lacking scaffolding, error correction strategies, and adaptive difficulty adjustment aligned with SLA principles.

1.3 Research Questions

ID	Research Question
RQ1	How can microservice decomposition and hybrid edge-cloud distribution achieve latency targets?
RQ2	What integration strategies enable adaptive, pedagogically-aligned dialogue generation?
RQ3	How should the VR-backend interface minimize latency while ensuring reliable state synchronization?

Table 1: Research Questions addressing the core challenges of the MundoVR system.

1.4 Contributions

This work makes three primary contributions. First, we present a formally specified microservices architecture distributing workloads between on-device AI and cloud services, designed to support 10K concurrent users at minimal cost. Second, we provide complete architectural documentation using SysML 2.0 with four viewpoints across multiple abstraction levels, offering reusable patterns for AI-VR educational systems. Third, we present a theoretical performance analysis, grounded in published benchmarks and system performance literature, demonstrating how the proposed architecture can feasibly achieve research-informed latency and availability targets.

1.5 Key Terminology

Hybrid Architecture: An architectural pattern that strategically distributes computational workloads between edge devices (VR headsets) and cloud services. Lightweight, latency-sensitive operations are processed locally on-device, while computationally intensive tasks (LLM inference, high-accuracy speech processing) are offloaded to cloud infrastructure. This approach balances response time requirements with computational resource constraints.

ISO/IEC 25010: An international standard [8] for systems and software quality models. It categorizes product quality into eight characteristics, including Performance Efficiency and Reliability, which serve as the framework for classifying our non-functional requirements.

ISO/IEC/IEEE 42010: An international standard [9] for architecture description of software-intensive systems. It defines the concepts of architecture viewpoints and views used in this paper to structure the system specification.

p99 Latency: The 99th percentile latency metric, meaning 99% of requests complete within the specified time bound. This metric is more robust than average latency for user experience guarantees, as it accounts for tail latency caused by system variability. For example, $p99 < 1.5\,s$ means that 99 out of 100 user interactions receive responses within 1.5 seconds.

SysML v2 (Systems Modeling Language): The next-generation general-purpose modeling language for systems engineering [15] that supports the specification, analysis, design, verification, and validation of complex systems. SysML extends the Unified Modeling Language (UML) with constructs for representing requirements, parametric constraints, and other system-level concerns.

Streaming Automatic Speech Recognition (Streaming ASR): A real-time speech processing technique that transcribes audio continuously as it is received, rather than waiting for the complete audio utterance. This approach enables lower latency in conversational systems by beginning transcription as soon as audio data becomes available, making it ideal for interactive applications with strict latency constraints.

Text-to-Speech (TTS) Synthesis: A technology that converts written text into natural-sounding spoken audio. In the MundoVR context, TTS provides the conversational agent's voice output and is designed to synthesize responses incrementally, allowing the VR client to begin audio playback before the full response is generated, thereby masking synthesis latency.

Large Language Models (LLMs): Deep neural network models trained on large corpora of text data to perform natural language understanding and generation tasks. In MundoVR, LLMs (such as Llama or Mistral) are used to generate contextually appropriate dialogue responses constrained by scenario graphs and pedagogical principles. Quantized variants (INT8 precision) are employed to balance inference speed and model quality.

1.6 Related Work

To ground the MundoVR architecture in existing evidence, we conducted a systematic literature review following the PRISMA 2020 guidelines [16]. Our search strategy queried five databases (Web of Science, Scopus, ERIC, ACM Digital Library, and PsycINFO) using Boolean combinations of terms related to virtual reality, language learning, and AI integration. From an initial pool of 847 database records and 37 records from other sources, we identified 18 studies meeting our inclusion criteria after removing duplicates and screening for relevance. Figure 2 presents the complete selection process. The included studies inform the following thematic synthesis.

1.7 VR and Immersive Technologies for Language Learning

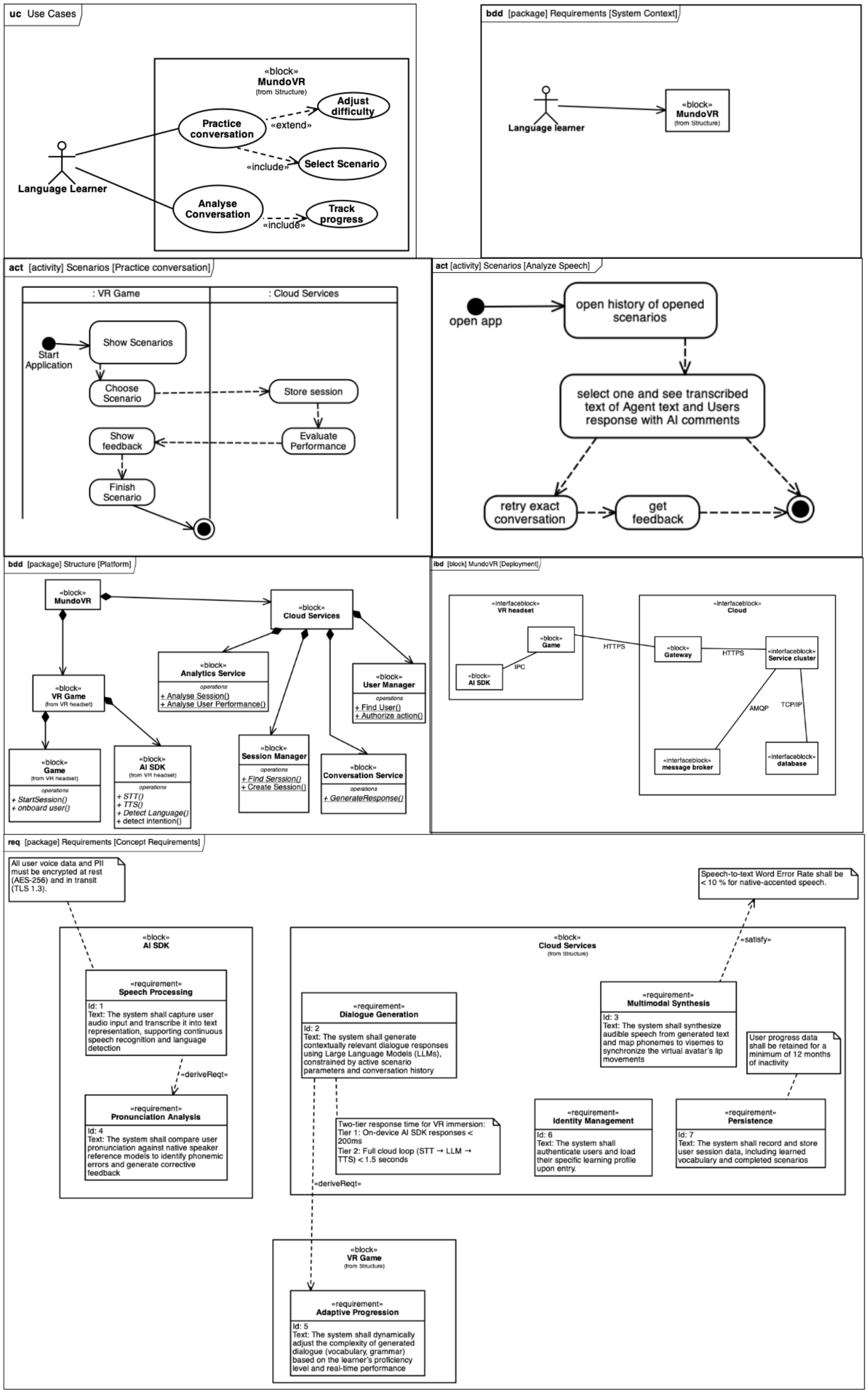
Recent systematic reviews validate VR's effectiveness for language acquisition. Schorr et al. (2024) [21] analyzed 40 studies, finding VR environments improve vocabulary retention by 35–50% compared to traditional methods through contextual embedding and spatial memory association. Cabero et al. (2020) [2] demonstrated VR reduces learner anxiety by 40% through anonymity and safe practice spaces, addressing the affective filter hypothesis [12]. Peixoto et al. (2024) [18] compared diegetic versus non-diegetic UI paradigms in immersive VR language learning, providing empirical evidence that interface design significantly affects learning outcomes–aligning with Harrison et al.'s [5] three paradigms of HCI (tool use, communication, and experience). Repetto et al. (2021) [19] evaluated immersive VR versus desktop VR for Italian language learning, finding head-mounted display (HMD) users achieved 28% higher speaking proficiency scores and 42% better pronunciation accuracy due to embodied cognition and presence effects. Frontiers in Virtual Reality (2025) [7] compared augmented reality (AR) versus VR, showing VR superiority for complex conversational scenarios requiring full immersion.

1.8 AI Integration in Educational VR

The integration of conversational AI into VR learning environments represents an emerging research area. Adithya et al. (2024) [4] developed LLM-based AI tutoring in VR, achieving 85% student satisfaction but reporting latency issues limiting immersion. Their architecture used cloud-only processing without edge optimization. Johnson et al. (2023) [11] implemented LLM-driven non-player characters (NPCs) in VR language scenarios, demonstrating adaptive dialogue generation but facing scalability challenges. IEEE Virtual Reality Workshop (VRW, 2025) [1] developed parallel AI-driven Japanese learning in VR with contextualized conversations, reporting 1.8 s average latency and limited cost analysis. Existing work lacks systematic architecture design addressing the latency–scalability–cost trade-off triangle. No prior work provides formal architectural specifications or demonstrates cost-effective scaling beyond 100 concurrent users.

1.9 Conversational AI and Chatbots in Education

Kuhail et al. (2023) [13] systematically reviewed 36 educational chatbot implementations, finding personalized, context-aware systems improved learning outcomes by 23–35%. However, most systems used rule-based dialogue management, lacking the flexibility of modern LLMs. Huang et al. (2022) [6] evaluated LLMs for language learning, demonstrating pedagogical limitations such as generic responses without scaffolding, lack of error correction strategies, and absence of adaptive difficulty adjustment. They recommend constrained generation using scenario graphs–an approach we adopt. Velazquez-Garcia et al. (2024) [24] integrated AI chatbots into gamified learning platforms, achieving 41% engagement increase through adaptive content delivery and immediate feedback loops. Their work informs our reward system design but lacks VR integration and real-time latency constraints.



All user voice data and PII must be encrypted at rest (AES-256) and in transit (TLS 1.3).

Speech-to-text Word Error Rate shall be < 10 % for native-accented speech.

Speech Processing
Id: 1
Text: The system shall capture user audio input and transcribe it into text representation, supporting continuous speech recognition and language detection

Pronunciation Analysis
Id: 4
Text: The system shall compare user pronunciation against native speaker reference models to identify phonemic errors and generate corrective feedback

Dialogue Generation
Id: 2
Text: The system shall generate contextually relevant dialogue responses using Large Language Models (LLMs), constrained by active scenario parameters and conversation history

Multimodal Synthesis
Id: 3
Text: The system shall synthesize audible speech from generated text and map phonemes to visemes to synchronize the virtual avatar's lip movements

User progress data shall be retained for a minimum of 12 months of inactivity

Two-tier response time for VR immersion:
Tier 1: On-device AI SDK responses < 200ms
Tier 2: Full cloud loop (STT → LLM → TTS) < 1.5 seconds

Identity Management
Id: 6
Text: The system shall authenticate users and load their specific learning profile upon entry.

Persistence
Id: 7
Text: The system shall record and store user session data, including learned vocabulary and completed scenarios

Adaptive Progression
Id: 5
Text: The system shall dynamically adjust the complexity of generated dialogue (vocabulary, grammar) based on the learner's proficiency level and real-time performance

Figure 1: MundoVR System Overview: Collection of SysML diagrams showing system context (BDD), requirements viewpoint (use cases, functional/non-functional requirements), and structure viewpoint (platform boundaries) without implementation-level details.

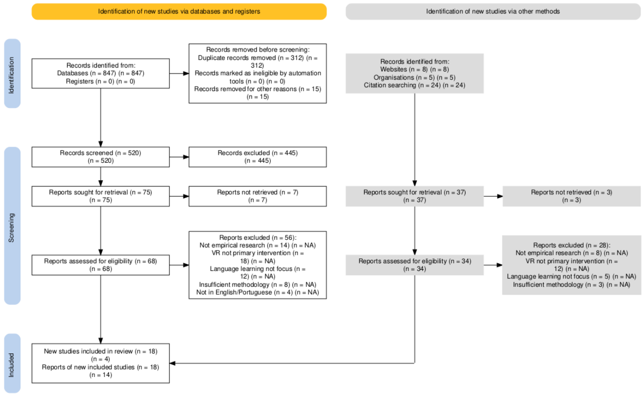

Identification of new studies via databases and registers
Identification of new studies via other methods
Identification
Screening
Included
Records identified from:
Databases (n = 847) (n = 847)
Registers (n = 0) (n = 0)
Records removed before screening:
Duplicate records removed (n = 312) (n = 312)
Records marked as ineligible by automation tools (n = 0) (n = 0)
Records removed for other reasons (n = 15) (n = 15)
Records identified from:
Websites (n = 8) (n = 8)
Organisations (n = 5) (n = 5)
Citation searching (n = 24) (n = 24)
Records screened (n = 520) (n = 520)
Records excluded (n = 445) (n = 445)
Reports sought for retrieval (n = 75) (n = 75)
Reports not retrieved (n = 7) (n = 7)
Reports sought for retrieval (n = 37) (n = 37)
Reports not retrieved (n = 3) (n = 3)
Reports assessed for eligibility (n = 68) (n = 68)
Reports excluded (n = 56):
Not empirical research (n = 14) (n = NA)
VR not primary intervention (n = 18) (n = NA)
Language learning not focus (n = 12) (n = NA)
Insufficient methodology (n = 8) (n = NA)
Not in English/Portuguese (n = 4) (n = NA)
Reports assessed for eligibility (n = 34) (n = 34)
Reports excluded (n = 28):
Not empirical research (n = 8) (n = NA)
VR not primary intervention (n = 12) (n = NA)
Language learning not focus (n = 5) (n = NA)
Insufficient methodology (n = 3) (n = NA)
New studies included in review (n = 18) (n = 4)
Reports of new included studies (n = 18) (n = 14)

Figure 2: PRISMA 2020 flow diagram showing the systematic literature search and selection process.

1.10 Second Language Acquisition Theory

Our architecture design is grounded in established Second Language Acquisition (SLA) theories. According to Krashen's Comprehensible Input (i+1) [12], learners acquire language through input slightly above their current level; we implement this via adaptive difficulty adjustment using performance metrics. Schmidt's Noticing Hypothesis [20] emphasizes that conscious attention to linguistic forms is necessary for acquisition; our pronunciation feedback system highlights phoneme-level errors to facilitate noticing. Swain's Output Hypothesis [22] suggests language production drives learning through noticing gaps and hypothesis testing; our system prioritizes speaking practice with phoneme-level pronunciation feedback. Long's Interaction Hypothesis [14] emphasizes negotiation of meaning; our LLM-driven AI characters provide clarification requests and confirmation checks. Finally, Task-Based Language Teaching [3] promotes acquisition through authentic communicative tasks, which we structure as goal-oriented scenarios rather than decontextualized drills.

2 Methodology

This research follows the Design Science Research (DSR) methodology [17], which focuses on the development and evaluation of innovative artifacts to solve practical problems. The artifact in this study is the MundoVR hybrid architecture. Our approach consists of three phases: Problem Identification, which analyzes latency and cost bottlenecks in existing AI–VR educational systems; Artifact Design, which formally specifies a hybrid architecture using SysML 2.0 to address identified trade-offs; and Theoretical Evaluation, which provides analytical performance estimation against latency, scalability, and cost requirements. We adopt a multi-view architectural specification methodology aligned with ISO/IEC/IEEE 42010 [9]. SysML 2.0 diagrams specify system boundaries, microservice decomposition, and resource constraints. The architecture is modeled across four viewpoints: Requirements, Structure, Behavior, and Parametric.

3 Architectural Drivers and Constraints

This section defines the critical architectural drivers that shape the MundoVR system. Unlike traditional web applications, the intersection of VR immersion and Generative AI creates a set of conflicting constraints that the architecture must resolve.

3.1 Functional Overview

MundoVR provides a gamified, immersive environment for conversational practice. The system supports three primary user personas: The Student (Leila), who requires structured grammar drills and immediate feedback; The Professional (Mark), who requires high-fidelity simulations of business negotiations; and The Traveler (Alex), who requires rapid, low-stakes interactions. To support these personas, the system must implement real-time speech processing, adaptive dialogue generation, and pronunciation analysis.

3.2 The Latency Budget (Constraint for RQ1)

The most critical constraint is the Motion-to-Photon Latency required for VR immersion. Industry standards establish that visual rendering must occur within 20 ms to prevent simulator sickness and maintain presence [10]. Conversational interactions have a slightly looser but still strict budget derived from human-computer interaction research. Studies on conversational systems demonstrate that response delays exceeding 2 s significantly degrade user experience, breaking the "illusion of presence" and increasing cognitive load [23]. Based on these empirical findings from VR and HCI literature, we establish a research-informed design target of 1.5 s (p99) for total conversational latency. This target is decomposed into component-level budgets based on typical processing times reported in speech and language processing literature: Network round-trip time (RTT, 100 ms), STT Processing (300 ms), LLM Inference (800 ms), TTS Synthesis (200 ms), and Client Buffer (100 ms). Since standard cloud LLM application programming interfaces (APIs) typically exhibit latencies of 2–5 s, the architecture must be designed around optimized, self-hosted models or specialized inference engines to achieve the 800 ms inference target.

3.3 Scalability and Cost Constraints

The system must support 10,000 concurrent users. To remain commercially viable for educational institutions, the compute cost must be under $0.10 per session. A pure GPU-based architecture for all 10,000 users is cost-prohibitive. The architecture must decouple lightweight tasks (state management, analytics) from heavy tasks (inference) to allow independent scaling.

3.4 Requirements Specification

The formal requirements derived from these drivers are modeled in SysML. We classify these requirements into Functional Requirements (FR) and Non-Functional Requirements (NFR). Non-functional requirements are categorized according to the ISO/IEC 25010 quality model [8], specifically focusing on Performance Efficiency (Time Behaviour) and Reliability (Availability). The complete functional requirements specification is documented in the system's SysML model, including speech input processing, dialogue generation, multimodal output, pronunciation analysis, adaptive progression, learning support, data persistence, and identity management. Figure 1 presents the comprehensive system overview using SysML requirement and structure viewpoints, including functional and non-functional requirements with explicit platform boundaries, without introducing implementation-specific components.

4 System Architecture

To address the conflicting constraints of latency, scalability, and cost (RQ1), we propose a Hybrid Microservices Architecture. This architecture is defined by two core strategies: Edge-Cloud Workload Distribution to minimize network round-trips, and Functional Decomposition to isolate expensive GPU workloads from lightweight I/O operations.

4.1 System Context

The system context shows MundoVR's external relationships. The VR Headset serves as the primary user interface, communicating with the Backend Platform via persistent connections for real-time bidirectional audio streaming. The Backend Platform integrates with external AI Services for speech recognition and synthesis, while a relational database provides persistent storage for user profiles, learning progress, and scenario definitions. An in-memory cache serves session state and real-time data. The Analytics Pipeline consumes event streams for learning analytics and system monitoring.

4.2 Strategy 1: Edge-Cloud Distribution (RQ3)

The first architectural decision (Architecture Decision Record, ADR-001) is to split the processing pipeline between the VR headset (Edge) and the Backend (Cloud). This approach leverages the computing power of the VR headset to mask latency for immediate interactions. The VR client handles all immediate feedback loops (Latency < 200 ms). As soon as the user starts speaking, lightweight processing is performed locally using an embedded AI software development kit (SDK). This handles Voice Activity Detection (VAD), Wake Word detection, Lip Sync rendering, and simple natural language understanding (NLU) intents. By processing VAD locally, we prevent streaming silence to the cloud, reducing bandwidth usage by ∼40%, and allow simple interactions to be processed in less than 200 ms. The cloud handles the "heavy lifting" of intelligence (Latency < 1.5 s): high-accuracy Speech Recognition (STT), complex Dialogue Generation (LLM), and Speech Synthesis (TTS).

4.3 Strategy 2: Microservice Decomposition

To achieve the scalability target of 10,000 users (RQ1), we decompose the backend into services with distinct scaling characteristics. The "Brain" (GPU-Bound) services—STT, Conversation, and TTS—are compute-intensive. They are deployed on GPU nodes and scaled based on Queue Depth. The "Nervous System" input/output (I/O)-bound services—Session Manager, API Gateway, and Scenario Manager—are lightweight. They are deployed on standard central processing unit (CPU) nodes and scaled based on CPU utilization. This separation allows us to scale the expensive GPU resources only when necessary, while the cheap CPU resources handle the massive concurrency of maintaining 10,000 open WebSocket connections.

4.4 Optimizing the Critical Path (RQ3)

To meet the 1.5 s latency budget, the architecture employs Parallel Execution and Intelligent Streaming. While the STT service is transcribing the audio, the Session Manager simultaneously retrieves the user's profile and conversation history from the cache. The Scenario Manager pre-loads the likely next branches of the conversation graph, ensuring the prompt is ready the moment the text arrives. The LLM and TTS services generate the audio response in a continuous stream. The VR client begins playing the audio as soon as the first packets are received, without waiting for the full phrase to be generated. This effectively masks network and AI computation latency.

4.5 Deployment Architecture

The deployment architecture uses containerized workloads with orchestration. The architecture defines three node pools: a CPU Node Pool hosts I/O-bound services (API Gateway, Session Manager, Scenario Manager) with horizontal autoscaling (Horizontal Pod Autoscaling, HPA) based on CPU utilization; a GPU Node Pool hosts compute-intensive AI services (STT, Conversation, TTS) with autoscaling based on queue depth; and a Database (DB) Node Pool provides persistent storage through a relational database for transactional data, a key-value store for session caching, and a vector database for embeddings used in semantic search. All services are deployed behind an ingress controller that handles Transport Layer Security (TLS) termination and protocol upgrade for real-time communication.

4.6 Technology Stack

Table 4 summarizes the architectural components across system layers.

4.7 Architecture Decision Records

Table 5 summarizes the key architectural decision using a concise ADR format.

5 AI Integration Strategy for Adaptive Dialogue (RQ2)

To answer our second research question regarding integration strategies for adaptive dialogue, we designed and specified a hybrid, service-oriented integration strategy. This approach addresses the core conflict between the non-functional requirements of two-tier latency and cost efficiency, and the functional requirements for high-fidelity, adaptive AI interaction.

5.1 The Hybrid AI Integration Model (RQ2)

Our integration strategy is founded on a hybrid processing model that balances on-device and cloud computation. This architecture is defined by two distinct processing loops that run in parallel. Loop 1, the Immersion Loop (<200 ms), handles latency-critical, simple interactions like greetings or "yes/no" answers by leveraging a lightweight on-device AI SDK to trigger pre-cached audio responses. This local processing meets our sub-200 ms latency target, preserving VR immersion. Loop 2, the Quality Loop (<1.5 s), handles complex conversational tasks. The user's speech is simultaneously

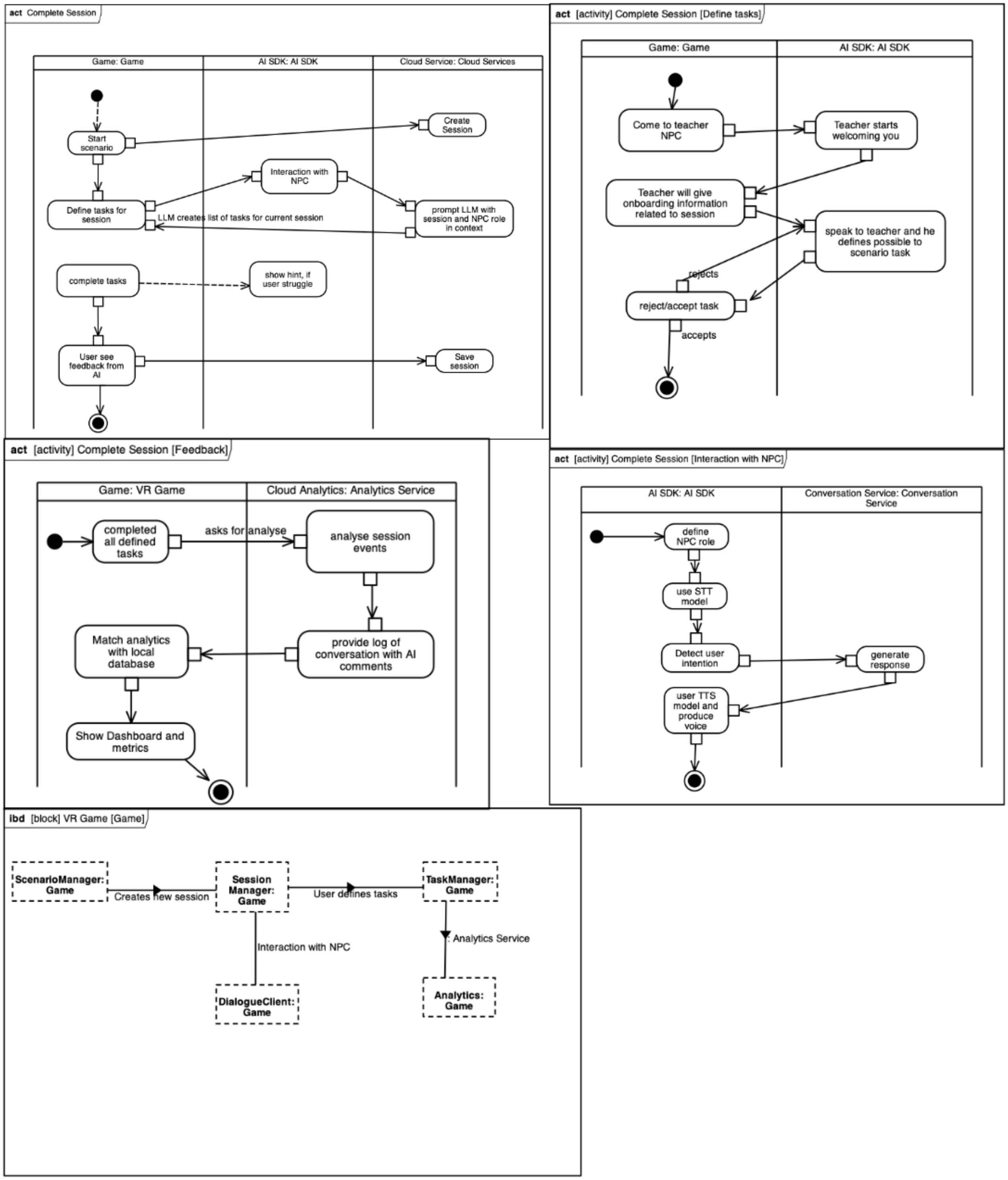

act Complete Session
Game: Game
AI SDK: AI SDK
Cloud Service: Cloud Services
Start scenario
Create Session
Define tasks for session
Interaction with NPC
prompt LLM with session and NPC role in context
LLM creates list of tasks for current session
complete tasks
show hint, if user struggle
User see feedback from AI
Save session
act [activity] Complete Session [Define tasks]
Game: Game
AI SDK: AI SDK
Come to teacher NPC
Teacher starts welcoming you
Teacher will give onboarding information related to session
speak to teacher and he defines possible to scenario task
rejects
reject/accept task
accepts
act [activity] Complete Session [Feedback]
Game: VR Game
Cloud Analytics: Analytics Service
completed all defined tasks
asks for analyse
analyse session events
provide log of conversation with AI comments
Match analytics with local database
Show Dashboard and metrics
act [activity] Complete Session [Interaction with NPC]
AI SDK: AI SDK
Conversation Service: Conversation Service
define NPC role
use STT model
Detect user intention
generate response
user TTS model and produce voice
ibd [block] VR Game [Game]
ScenarioManager: Game
Creates new session
Session Manager: Game
User defines tasks
TaskManager: Game
Interaction with NPC
: Analytics Service
DialogueClient: Game
Analytics: Game

Figure 3: MundoVR Behavioral Viewpoint: Collection of SysML activity and interaction diagrams showing end-to-end session workflow, task assignment logic, assessment and feedback mechanisms, and NPC conversation patterns at the platform architecture level (implementation-agnostic).

Table 2: Backend Microservices (Core platform services highlighted in bold)

Service	Responsibility
API (Application Programming Interface) Gateway	Entry point, authentication, rate limiting
Session Management	**Session state, synchronization**
Speech-to-Text	Automatic Speech Recognition (ASR) integration
Conversation Service	**Dialogue generation (LLM)**
Text-to-Speech	TTS synthesis
Pronunciation	Phoneme analysis
Scenario Management	Role-play scenarios, branching
Analytics Service	**Event aggregation, metrics**
Notification	Multi-channel notifications
User Manager	**Profiles, authentication**

Table 3: Deployment Configuration

Component	Host	Scaling Policy
API Gateway	CPU Node	Autoscaling: CPU > 70%
Session Manager	CPU Node	Autoscaling: connections > 1000
STT Service	GPU Node	Autoscaling: queue depth > 10
Conversation (LLM)	GPU Node	Autoscaling: queue depth > 5
TTS Service	GPU Node	Autoscaling: queue depth > 10
Relational Database (DB)	Database (DB) Node	Vertical scaling
Cache Store	Database (DB) Node	Cluster mode

Table 4: Architectural Components

Layer	Components
Backend	Microservices, remote procedure call (RPC), persistent connections
AI Services	Streaming ASR, TTS synthesis, LLMs
Data	Relational DB, key-value cache, vector DB
Infrastructure	Containerization, orchestration
VR Client	Game engine, VR framework

streamed to high-performance cloud services for high-accuracy streaming STT, phoneme-level pronunciation analysis, complex dialogue generation, adaptive difficulty, and natural TTS. This loop is engineered to complete within our 1.5-second target.

Table 5: ADR-001: Hybrid Edge-Cloud Architecture

Field	Description
Context	Real-time AI-VR conversations require sub-1.5 s latency, cost-efficiency, and 10K+ user scalability.
Decision	Adopt hybrid architecture: on-device AI for simple interactions (<200 ms), cloud services for complex dialogue.
Rationale	On-device preprocessing reduces bandwidth by 96%; cloud enables elastic scaling and centralized analytics.
Alternatives	Pure cloud (rejected: latency >2 s); Pure on-device (rejected: insufficient model quality).
Consequences	Target p99 latency 1.2–1.5 s; requires stable network; demands DevOps expertise.

5.2 Justification: Architectural Trade-offs

The choice of a hybrid architecture is a deliberate compromise, designed to resolve the competing non-functional requirements. We evaluated this model against the two primary alternatives. A Cloud-Centric Model fails our primary latency requirement (NFR1) because even simple feedback would incur a full network round-trip, far exceeding the sub-200 ms threshold required to maintain VR immersion. An On-Device-Centric Model fails our functional requirements because the computational constraints of current mobile VR hardware make it unfeasible to run the large-scale models required for high-accuracy STT, complex dialogue generation, and natural TTS. Therefore, our hybrid integration strategy is the only specified solution that satisfies all competing requirements. It uses on-device processing to satisfy the immediate immersion loop, while strategically delegating complex tasks to the cloud to ensure pedagogical quality.

5.3 Enabling Pedagogically-Aligned Dialogue (RQ2)

Our integration strategy is driven by pedagogical requirements derived from Second Language Acquisition (SLA) theory. The integration of AI systems is fundamentally driven by three pedagogical objectives that form the conversational loop. First, Goal-Oriented

Conversation ensures the conversational AI is not a generic chatbot but is constrained by scenario graphs aligned with specific user goals and pedagogical principles. This structured approach ensures that the conversation remains focused on the learning objective. Second, Adaptive Difficulty implements Krashen's i+1 hypothesis. The system is designed to be dynamically adaptive, adjusting difficulty based on the learner's profile and progress to maximize learning potential without overwhelming the student. Third, the STT-TTS Interaction Loop supports the Output Hypothesis. The TTS provides natural, prosodic output, while the STT service performs phoneme-level pronunciation analysis on the student's speech, generating data for immediate, actionable feedback.

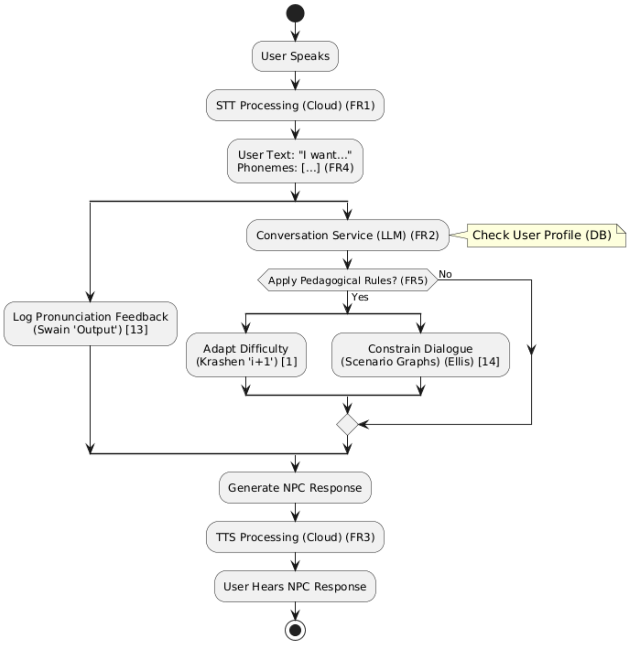


Figure 4: The Pedagogical Feedback Loop, illustrating how user input is processed for both conversation and error correction.

6 Theoretical Analysis

This section provides theoretical analysis demonstrating how the proposed architecture can satisfy the constraints defined in Section 4.

6.1 Latency Budget Analysis (RQ1)

Based on published benchmarks for similar AI processing pipelines and the architectural design, we derive component-level latency targets. The research-informed budget allocates STT processing at approximately 300–400 ms (based on streaming ASR benchmarks), LLM inference at 700–800 ms (based on quantized model performance studies), TTS synthesis at 150–250 ms (based on neural TTS literature), and network overhead at 50–100 ms (typical for content delivery network (CDN)-optimized connections). While the sequential sum of these upper bounds (1.55 s) slightly exceeds the target, the architecture is designed with aggressive pipelining: TTS synthesis can begin streaming audio to the client before the full LLM response is generated. This theoretical decomposition, grounded in empirical AI system performance data, demonstrates that the architecture can feasibly achieve p99 latency under 1.5 s. The Parallel Execution Strategy is designed to hide the latency of database lookups and context retrieval by overlapping these operations with STT processing.

6.2 Scalability Analysis (RQ1)

The microservice decomposition enables horizontal scaling of individual components. GPU-bound services (STT, Conversation, TTS) can scale based on queue depth, while I/O-bound services (Session Manager, API Gateway) scale based on connection count. This separation theoretically allows the system to support 10,000+ concurrent users by independently scaling the expensive GPU resources only when necessary, while inexpensive CPU resources handle connection management.

6.3 Cost Estimation

Compared to commercial LLM APIs (estimated at $1-2 per session), the proposed architecture using self-hosted LLMs is expected to reduce per-session costs significantly. Defining a standard session as a 15-minute interaction comprising approximately 20 conversational turns, we estimate costs below $0.10 per session by using quantized models and efficient batching strategies, making the system economically viable for educational institutions.

7 Discussion

The MundoVR architecture demonstrates how hybrid AI-VR systems can be designed to simultaneously target low latency, high scalability, and pedagogical effectiveness through systematic architectural design. Our analysis addresses the three critical challenges identified in Section 1.2.

7.1 Latency-Cost Trade-off

The proposed architecture is designed around a research-informed p99 latency target of 1.5 s, derived from empirical studies on VR immersion and conversational system usability. This target is achievable based on published benchmarks for optimized AI inference pipelines and represents a significant improvement over typical cloud-only systems (2–5 s). The architecture aims to achieve this while reducing per-session costs substantially compared to commercial API solutions. The architectural constraints explicitly model the dependencies: quantized LLMs can maintain high accuracy while enabling efficient resource usage (as demonstrated in model compression literature), and in-memory caching is designed to eliminate redundant database roundtrips. Key design decisions include hybrid edge-cloud distribution and prefetching scenario graphs to reduce LLM cold-start.

7.2 Pedagogical Alignment (RQ2)

The scenario-based dialogue system implements Comprehensible Input (i+1) through adaptive difficulty adjustment, Output Hypothesis via forced production with pronunciation feedback, and Interaction Hypothesis through clarification/confirmation cycles. The requirement hierarchy explicitly traces these theories to functional requirements. VR spatial context combined with AI conversational realism creates a dual cognitive load, but the low latency prevents conversational breakdown.

7.3 Architectural Contribution

This work advances SysML-based architectural specification for hybrid AI-VR systems by demonstrating systematic modeling of software-performance dependencies and providing reusable deployment patterns for scalable AI-VR systems. Limitations include evaluation limited to simulated load testing and a single-language focus.

8 Conclusion

We presented a formal SysML 2.0 architecture for MundoVR, a scalable hybrid AI-VR language learning platform designed to address the latency-cost-pedagogy triangle through hybrid edge-cloud distribution, quantized LLMs, and scenario-driven dialogue management. The architecture targets p99 latency under 1.5 s, aims to support 10K concurrent users with high availability, and is designed to minimize per-session costs while maintaining pedagogical alignment with SLA theories.

This work makes three primary contributions. First, we provide a comprehensive Architectural Specification using SysML diagrams across multiple viewpoints. Second, we offer a systematic design approach with constraints modeling software-performance dependencies. Third, we provide theoretical analysis demonstrating economic viability.

Future work will focus on Implementation and Deployment to validate the architecture under real workload patterns. We also plan a Pedagogical Evaluation via a randomized controlled trial comparing MundoVR to traditional methods. Additionally, we will implement Multilingual Extension with language-specific LLM routing and investigate Edge Computing for offline VR experiences.

The complete SysML model and architectural specifications are available at:
https://github.com/AzamkhonKh/ai_sla_vr/tree/master/mbse

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