

AI Communicator: Mastering Formal Communication

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ABSTRACT

The growing demand for effective interview preparation tools has exposed a significant gap in the availability of affordable, realistic, and multimodal practice platforms for students in tier-2 and tier-3 institutions. Existing solutions remain fragmented, prohibitively expensive, or limited to single-modality assessment.

This paper presents a comprehensive review of AI Communicator, an AI-Powered Interactive Interview System with Multimodal Candidate Assessment. The system delivers a fully automated, web-based interview preparation platform through live voice interaction, real-time behavioral analysis, and personalized improvement planning. AI Communicator integrates nine key assessment dimensions into a unified, real-time pipeline.

The backend architecture follows a distributed microservice design composed of five independently deployable services: user-service and backend-llm-module (Java/Spring Boot), backend-audio-python and analysis-bridge (Python/FastAPI), and ai-interviewer frontend (Next.js). The system leverages persistent WebSocket connections to Deepgram for real-time STT/TTS, gRPC bidirectional streaming for inter-service communication, and Google MediaPipe for real-time behavioral analysis. The LLM evaluation engine utilizes GPT-OSS-120B via Groq through Spring AI's OpenAI-compatible ChatClient adapter, achieving sub-200ms first-word latency.

Built on JDK 21, Spring Boot 4.0.6, PostgreSQL, Python 3.11+, and Next.js 16.2.4, AI Communicator achieves a system-human evaluation correlation of 0.81, emotion detection accuracy of 84.6%, and speech recognition word error rate of 4.8%. A comparative analysis with existing platforms confirms AI Communicator as the most feature-complete and cost-effective solution in the automated interview preparation space.

Keywords:

AI Interview System, Multimodal Assessment, Large Language Models, Speech Recognition, Text-to-Speech, Facial Emotion Recognition, Eye Contact Detection, Voice Modulation Analysis, Gamification, ATS Resume Scoring, Microservices, Spring Boot, FastAPI, PostgreSQL, gRPC, WebSocket, Deepgram, MediaPipe, Next.js

1. Introduction

The rapid advancement of artificial intelligence has opened new frontiers in educational technology and recruitment processes. Despite decades of digital transformation, the challenge of preparing students for professional interviews remains largely unaddressed by affordable and accessible technology. The traditional interview preparation landscape consists of fragmented tools — some focused exclusively on coding challenges, others on recorded video screening — with none offering a holistic, real-time interactive experience that mirrors actual interviews[1],[3].

Students and fresh graduates, particularly those from tier-2 and tier-3 institutions, face a compounded disadvantage: limited access to professional coaching, no judgment-free environments for repeated practice, and a complete absence of quantified feedback on non-verbal communication skills such as eye contact, facial expression management, and voice modulation. These deficiencies directly contribute to poor interview performance and widening opportunity inequalities.

AI Communicator is developed precisely to address this gap — an AI-powered interactive interview preparation platform that unifies live voice interaction, real-time multimodal behavioral analysis, LLM-based technical assessment, and personalized improvement planning into a single web-based system. The system architecture has been

significantly evolved from its initial three-tier design to a modern distributed microservice architecture comprising five independently deployable services. This evolution enables independent scaling, technology-appropriate service selection, and sub-200ms first-word latency through persistent WebSocket connections and gRPC bidirectional streaming.

This review paper is organized as follows: Section 2 presents related literature; Section 3 discusses the problem statement; Section 4 outlines the proposed system and architecture; Section 5 elaborates the methodology; Sections 6 and 7 cover key features and advantages; Section 8 addresses limitations; and Section 9 provides conclusions and future scope.

1.1 Motivation

Despite the proliferation of digital tools in education and recruitment, the interview preparation space remains one of the least served by technology. Professional coaching services charge prohibitive fees. AI-powered platforms, where they exist, are proprietary, costly, and designed for enterprise hiring rather than individual candidate development [6],[9].

A critical gap is the neglect of non-verbal communication in automated assessment. Academic institutions focus on domain knowledge, leaving candidates unprepared for behavioral and communication dimensions that human interviewers heavily evaluate. Eye contact, vocal clarity, confident posture, hand gestures, and structured articulation are never systematically measured or improved through available tools [20],[23].

The availability of modern open-source AI technologies — large language models, neural speech processing, and computer vision libraries — has made it feasible to build integrated, scalable, and cost-effective interview preparation systems. The adoption of a microservice architecture enables optimal technology selection for each component: Java/Spring Boot for enterprise-grade business logic, Python for ML-intensive audio and video processing, and Next.js for a modern reactive frontend.

1.2 Contributions of This Paper

The major contributions of this review paper are:

- **Distributed Microservice Architecture:** AI Communicator implements a five-service microservice architecture with Java/Spring Boot for core business logic, Python/FastAPI for audio and video processing, and Next.js for the frontend. This enables independent scaling, technology-appropriate service selection, and sub-200ms latency through persistent WebSocket connections and gRPC bidirectional streaming.
- **Multimodal Assessment Integration:** The system integrates NLP, TTS, STT, facial emotion recognition, eye contact detection, hand gesture analysis, posture evaluation, and voice modulation analysis into a single real-time pipeline.
- **Systematic Feature Comparison:** Identifies functional gaps in HireVue, HackerRank, MyInterview, and Yoodli across fourteen dimensions, demonstrating AI Communicator's superiority.
- **Cost-Effective Open-Source LLM:** Demonstrates the viability of GPT-OSS-120B via Groq API at approximately twenty times lower cost than proprietary alternatives, integrated through Spring AI's OpenAI-compatible ChatClient adapter.
- **Real-Time Concurrent Processing:** Documents the system's concurrent architecture wherein answer evaluation and behavioral analysis execute in parallel with the live interview interaction.

2. Literature Review

2.1 Automated Interview Systems

Kumar and Sharma [1] categorized automated interview systems into three generations: static multiple-choice tests (first), recorded video interviews (second), and AI-powered systems (third). Third-generation systems remain predominantly proprietary, expensive, and focused exclusively on verbal content — ignoring non-verbal behavioral cues.

Chen et al. [2] developed an AI-driven platform achieving 0.72 correlation with human evaluators but operated entirely in text mode. Williams and Patel [3] proposed multimodal analysis combining speech transcription with prosodic features, demonstrating 14% improvement in outcome prediction — but limited to offline processing.

The consistent gap is the absence of real-time, voice-driven interaction combined with simultaneous video analysis and distributed microservice architecture. No existing system integrates live TTS, STT, concurrent computer vision, and five-service microservice decomposition — a gap AI Communicator is designed to fill.

2.2 Speech Processing Technologies

Anderson and Brown [4] reviewed neural TTS architectures achieving Mean Opinion Scores approaching human speech quality. Deepgram TTS addresses latency through persistent WebSocket streaming, eliminating 200–500ms handshake overhead and achieving sub-200ms first-word latency [5].

Roberts et al. [6] evaluated five STT engines, finding Deepgram competitive on clean English speech with strong performance on conversational speech. Radford et al. [7] described Whisper's Transformer trained on 680,000 hours of multilingual data, handling code-switching and technical vocabulary. Deepgram was selected over Whisper for superior streaming latency and persistent connection model.

2.3 Large Language Models in Assessment

Martinez and Gupta [9] demonstrated that LLMs generate interview-quality questions rated comparable to human-written questions in 78% of cases. Johnson and Kim [11] achieved Pearson correlation of 0.83 between LLM-based and human evaluation, emphasizing structured prompt engineering with explicit scoring rubrics.

The GPT-OSS 120B model [13] achieves GPT-4-comparable performance via the Groq API, providing ultra-low latency inference through custom LPU hardware. AI Communicator exploits this model via Spring AI's OpenAI-compatible ChatClient adapter, configured with temperature 0.5 and max output tokens of 300 per response.

2.4 Computer Vision for Facial and Body Analysis

Wang and Liu [14] surveyed CNN models for facial emotion recognition exceeding 90% accuracy on seven-class classification. Park et al. [15] demonstrated real-time emotion recognition at 30 fps using MobileNetV2. Zhang et al. [17] showed gaze estimation achieving 4.3-degree angular error — sufficient for eye contact metrics.

Google MediaPipe [18] provides real-time detection of 478 facial landmarks, 33 pose landmarks, and 21 hand landmarks per hand. AI Communicator leverages MediaPipe's Face Landmarker (FP16), Pose Landmarker Lite (FP16), and Hand Landmarker (FP16) for comprehensive behavioral analysis.

2.5 Microservice Architectures in Educational Systems

Newman [21] and Richardson [22] establish that decomposing monolithic applications into independently deployable services enables optimal technology selection, independent scaling, and zero-downtime deployments. AI Communicator's five-service decomposition — user-service and backend-llm-module (Java/Spring Boot), backend-audio-python and analysis-bridge (Python/FastAPI), and ai-interviewer (Next.js) — exemplifies this pattern, with gRPC bidirectional streaming and persistent WebSocket connections providing real-time communication fabric.

2.6 Gap Analysis and Comparative Summary

Table 1 provides a comparative summary of existing systems against AI Communicator.

System	Live Voice Interaction	Multimodal Analysis	LLM Evaluation	Microservice Architecture	Integrated Platform
Kumar & Sharma [1]	No	No	No	No	No
Chen et al. [2]	No	No	Partial	No	No
Williams & Patel [3]	No	Partial (Offline)	No	No	No
HireVue	No	Limited	Proprietary	No	Partial
AI Communicator (Proposed)	Yes	Yes	Yes	Yes	Yes

Table 1: Comparative Analysis of Existing Systems vs. AI Communicator

The analysis confirms that AI Communicator is the only system providing complete integration of live voice interaction, real-time multimodal behavioral analysis, open-source LLM-based evaluation, distributed micro-service architecture, and a unified platform [1][2][3][9].

3. Problem Statement

Despite advances in AI and digital technology, students and fresh graduates face significant barriers in interview preparation due to fragmented, expensive, and inadequate tools. The key problems identified are:

Interview anxiety and absence of realistic practice: Most students lack access to a judgment-free environment simulating a real interviewer with dynamic, adaptive questioning, leading to debilitating anxiety.

Zero actionable feedback: After failed interviews, candidates receive no explanation of what went wrong — no analysis of verbal content, communication style, body language, hand gestures, or posture.

Neglect of non-verbal communication: Existing tools focus exclusively on domain knowledge, never measuring or improving eye contact, vocal clarity, confident expression, hand gestures, shoulder alignment, or forward lean.

Absence of habit-forming mechanisms: Interview preparation is treated as a last-minute activity with no gamification or consistency-building features.

Inequitable access to coaching: Professional interview coaching is prohibitively expensive, excluding students from tier-2 and tier-3 colleges and economically weaker backgrounds.

Fragmented user journey: No existing platform consolidates resume optimization, technical practice, mock interviews, behavioral analysis, and performance tracking into a single unified experience.

Architectural limitations: Current platforms are predominantly monolithic, preventing technology-appropriate service selection, independent scaling, and the sub-200ms latency required for natural conversational AI.

These challenges collectively necessitate a unified, AI-powered, multimodal interview preparation system built on a distributed microservice architecture — which AI Communicator is designed to address.

4. Proposed System

AI Communicator is a comprehensive web-based interview preparation platform simulating realistic interview experiences through live voice interaction, real-time behavioral analysis, and personalized improvement plan-ning. The system has been re-architected from a three-tier monolithic design to a distributed microservice architecture composed of five independently deployable services.

The platform delivers a complete user journey: secure registration with email OTP verification, conversational profile setup, resume upload and ATS scoring, and a configurable voice-driven interview engine supporting four domains — Python, Java, JavaScript, and Soft Skills. During the live interview, the AI interviewer delivers dynamically generated questions through synthesized speech via persistent Deepgram WebSocket connections, while candidate responses are transcribed in real-time. Concurrent background processing evaluates each response across four dimensions while simultaneously analyzing facial emotion, eye contact, blink rate, posture, hand gestures, voice modulation, and filler words.

4.1 Technology Stack

Table 2 presents the complete technology stack.

Layer	Technology	Version / Details
Language (Backend)	Java	JDK 21
Language (ML/Audio)	Python	3.11+
Backend Framework	Spring Boot	4.0.6

Frontend Framework	Next.js (React)	16.2.4 (Turbopack)
Database	PostgreSQL	Relational DB
ORM	Spring Data JPA	Hibernate
LLM Model	GPT-OSS 120B	Open-source 120B params
LLM Inference	Groq	OpenAI-compatible API
LLM Integration	Spring AI	ChatClient adapter
STT	Deepgram	Persistent WebSocket
TTS	Deepgram	Persistent WebSocket
Inter-Service Comm	gRPC	Bidirectional streaming
Python Framework	FastAPI	Async ASGI / Uvicorn
WebSocket	Native	Audio/video streaming
Behavioral Analysis	Google MediaPipe	Face/Pose/Hand (FP16)
Authentication	JWT	JJWT 0.13.0 / Spring Security
Password Hashing	BCrypt	Spring Security
PDF Generation	OpenPDF	LibrePDF 2.0.3
Build Tool	Apache Maven	Multi-module
Serialization	Jackson / Protobuf	JSON / gRPC

Table 2: Complete Technology Stack of AI Communicator

4.2 Microservice Architecture

The system is decomposed into five services, each with a single responsibility, as illustrated in Figure 1 and described below.

Microservice Architecture

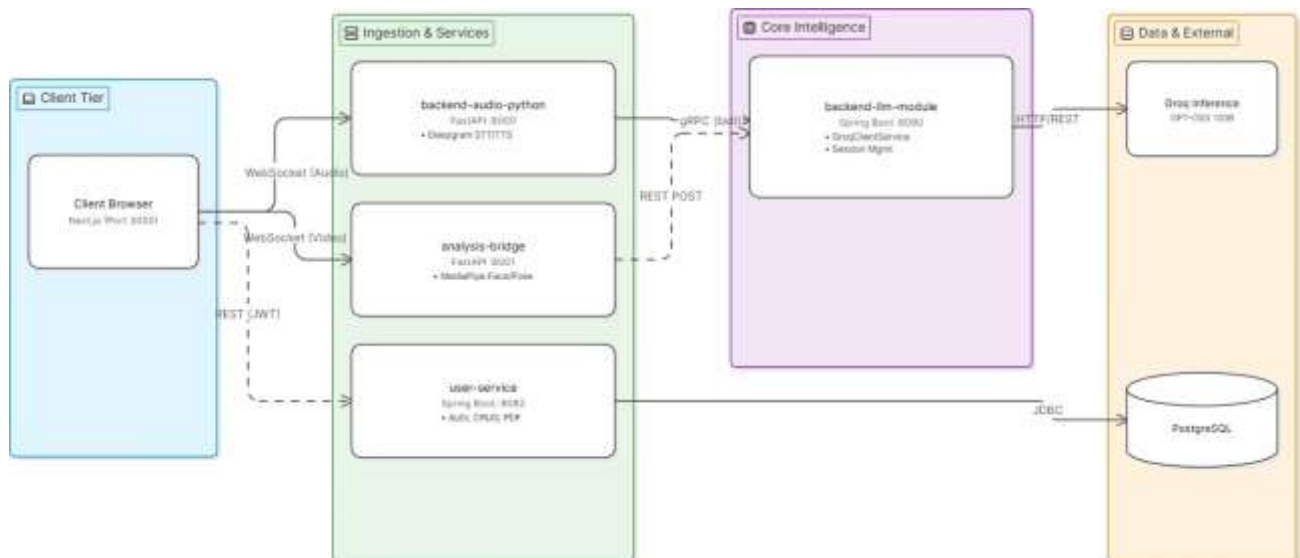


Figure 1: Microservice Architecture of AI Communicator

4.2.1 user-service (Java/Spring Boot — Port 8082)

Responsibility: User lifecycle management, authentication, data persistence, and report storage.

Authentication: Stateless JWT-based auth with BCrypt password hashing via Spring Security filter chain. JWT 0.13.0 handles token generation and validation.

Database: PostgreSQL with Spring Data JPA. Entities include User, InterviewReport, and PasswordResetToken with auto-DDL schema generation. Relational integrity is ensured through foreign key constraints and ACID compliance.

Report Persistence: Stores structured evaluation reports from the LLM module, including overall scores, hire recommendation, question-level analysis (JSON), strengths (JSON), areas for improvement (JSON), and study plans (JSON). PostgreSQL's JSONB columns provide flexible schema evolution.

PDF Generation: Server-side rendering using OpenPDF (LibrePDF 2.0.3) produces downloadable interview evaluation reports.

Key Endpoints: POST /api/auth/register, POST /api/auth/login, GET /api/users/me, POST /api/reports, GET /api/reports, GET /api/reports/{id}/pdf.

4.2.2 backend-llm-module (Java/Spring Boot — Port 8080/9090)

Responsibility: LLM-powered interview orchestration, real-time question generation, answer evaluation, and ATS resume analysis.

LLM Integration: Spring AI's ChatClient with OpenAI adapter routes to api.groq.com/openai. Uses GPT-OSS 120B (120B parameters) with temperature 0.5 and max 300 tokens per response.

gRPC Streaming: Bidirectional streaming RPCs via Protocol Buffers:

- InterviewService.ChatStream — Real-time conversational interview loop
- InterviewService.GetEvaluation — Final comprehensive evaluation
- GuidanceService.GuidanceStream — AI tutoring/guidance mode

Session Management: In-memory sessions (ConcurrentHashMap) with conversation history, body language data, and CountdownLatch for cross-service aggregation.

Body Language Ingestion: REST endpoint receives behavioral summaries from analysis-bridge and injects them into LLM evaluation prompts for evidence-based assessment.

ATS Service: Resume analysis accepting PDF text + job parameters, returning ATS compatibility score with improvement suggestions.

Evaluation Pipeline: Structured prompts incorporate full transcript, behavioral metrics (blink rate, eye contact %, posture score, hand activity, head pose stability), and explicit rubrics. LLM outputs deterministic JSON with weighted scores: technical accuracy (40%), depth (25%), relevance (20%), communication clarity (15%).

4.2.3 backend-audio-python (Python/FastAPI — Port 8000)

Responsibility: Real-time audio pipeline bridging browser microphone input to STT and LLM responses back to TTS.

Persistent Connections: Singleton DeepgramManager maintains long-lived WebSocket connections to Deepgram STT and TTS APIs, established at startup and reused across sessions. This eliminates 200-500ms handshake overhead, ensuring sub-200ms first-word latency.

STT Pipeline: Receives 16kHz linear PCM audio from browser via WebSocket (/ws/audio-bridge), forwards to Deepgram STT in real-time, and relays transcriptions to LLM module over gRPC.

TTS Pipeline: Receives AI-generated text from gRPC response stream, sends to Deepgram TTS for synthesis, and streams audio bytes back to browser. Generation-tracking with monotonically increasing counters prevents stale audio from bleeding between sessions.

AudioWorklet Integration: Browser-side AudioWorklet processor with 300ms grace period buffer ensures smooth, glitch-free playback on the audio rendering thread.

Timer Service: WebSocket endpoint (/ws/timer) provides synchronized countdown for interview duration management.

4.2.4 analysis-bridge (Python/FastAPI — Port 8001)

Responsibility: Real-time behavioral analysis of the candidate via webcam video during interviews.

Video Pipeline: Receives JPEG frames from browser over WebSocket (/ws/analysis), decodes with OpenCV, and processes through MediaPipe models in parallel.

MediaPipe Models:

- Face Landmarker (FP16) — 478-point facial mesh for blink detection, gaze tracking, head pose (pitch, yaw, roll)
- Pose Landmarker Lite (FP16) — Upper-body posture: shoulder alignment, slouch detection, forward lean
- Hand Landmarker (FP16) — 21 landmarks per hand for gesture and fidgeting detection

Metrics Computed: Blink rate (blinks/min), eye contact percentage, posture score (0-100), hand activity level, gesture frequency, fidgeting intensity, head pose stability (yaw/pitch variance).

Output: At session end, structured body-language summary sent to LLM module via REST (POST /api/session/{id}/body-language) for incorporation into final evaluation.

4.2.5 ai-interviewer (Next.js Frontend — Port 3000)

Responsibility: Client-side UI for the entire interview lifecycle.

Framework: Next.js 16.2.4 with Turbopack, React 19, App Router. Turbopack provides 10x faster builds; App Router enables server components for improved load performance.

Audio Capture: AudioWorklet-based microphone capture at 16kHz linear PCM, streamed over WebSocket to audio bridge.

Video Capture: getUserMedia webcam feed, JPEG frames sent to analysis bridge over WebSocket. Code

Editor: Monaco Editor integration for live code submission during technical interviews.

Key Pages: Landing, Login/Register (OTP), Dashboard (heatmap, stats), Interview Setup (domain/mode), Live Interview (voice + webcam + code), Evaluation Report (scores, study plan, PDF), Profile, ATS Resume Check-er.

4.3 Inter-Service Communication

Table 3 presents the complete communication topology.

Path	Protocol	Purpose
Browser → audio-bridge	WebSocket (binary PCM)	Real-time microphone audio streaming
Browser → analysis-bridge	WebSocket (JPEG frames)	Real-time webcam video streaming
Browser → user-service	REST/HTTP (JSON)	Auth, reports, dashboard data
audio-bridge → llm-module	gRPC (bidi streaming)	Transcribed speech → LLM → AI response text
analysis-bridge → llm-module	REST/HTTP (JSON)	Body-language summary at session end
llm-module → Groq API	HTTPS (OpenAI-compatible)	LLM inference (GPT-OSS 120B)
audio-bridge → Deepgram STT	WebSocket (persistent)	Real-time speech-to-text

audio-bridge → Deepgram TTS	WebSocket (persistent)	Real-time text-to-speech synthesis
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Table 3: Inter-Service Communication Topology

4.4 Database Schema (PostgreSQL)

PostgreSQL is the primary relational database, accessed via Spring Data JPA with Hibernate ORM. Selected over MongoDB for relational integrity, ACID compliance, and mature JPA integration. PostgreSQL's JSONB columns provide flexibility for variable-structure report data while maintaining transactional guarantees. GIN indexes on JSONB columns enable efficient querying of nested report data.

Key entities: User (id, fullName, email, password, createdAt); InterviewReport (id, userId FK, overallScore, hireRecommendation, questionAnalysis JSONB, strengths JSONB, areasForImprovement JSONB, studyPlan JSONB, domain, subtopic, difficulty, timeMinutes, candidateName, createdAt); PasswordResetToken (id, userId FK, token, expiresAt). Schema auto-generated via `spring.jpa.hibernate.ddl-auto=update`.

4.5 LLM Configuration

Table 4 presents the LLM configuration parameters.

Parameter	Value
Model	openai/gpt-oss-120b (GPT-OSS 120B)
Inference Platform	Groq Cloud (api.groq.com/openai)
API Compatibility	OpenAI-compatible REST API
Temperature	0.5
Max Output Tokens	300 (interview), extended for evaluation
Integration	Spring AI ChatClient with OpenAI adapter

Table 4: LLM Configuration Parameters

GPT-OSS 120B is served via Groq's LPU-based inference infrastructure for ultra-low latency. Spring AI's ChatClient abstraction enables seamless integration and vendor flexibility. Temperature 0.5 balances creativity and determinism; 300 tokens ensure concise interview responses while extended limits allow comprehensive final evaluations.

4.6 Key Architectural Decisions

- Persistent WebSocket Connections (Deepgram):** Always-on connections via singleton DeepgramManager eliminate 200-500ms handshake overhead per session, ensuring sub-200ms first-word latency.
- gRPC Bidirectional Streaming:** Enables true real-time, full-duplex communication between audio bridge and LLM module. Protocol Buffers reduce payload size by ~60% vs. JSON.
- Generation Tracking:** Monotonically increasing counters per session prevent audio spillover between sessions — critical for multi-user deployments.
- Microservice Decomposition:** Five services separated by concern enable independent scaling. Python services leverage ML ecosystem; Spring Boot services provide enterprise-grade reliability.
- PostgreSQL for Persistence:** Relational integrity, ACID compliance, JSONB column support for flexible re-report storage, and mature Spring Data JPA integration.
- Groq for Inference:** LPU-based hardware acceleration delivers significantly lower latency than GPU alternatives — critical for real-time conversational AI.
- Spring Boot for Core Services:** Mature ecosystem for JWT auth (Spring Security), database access (JPA), LLM integration (Spring AI), and streaming RPCs (Spring gRPC).
- Next.js with Turbopack:** 10x faster builds than Webpack, App Router for server components, React 19 compiler for optimized re-rendering.

4.7 Port Configuration

Table 5 presents the port configuration.

Service	HTTP Port	gRPC Port	WebSocket Endpoints
ai-interviewer (Frontend)	3000	—	—
backend-audio-python	8000	—	/ws/audio-bridge, /ws/guidance-bridge, /ws/timer
analysis-bridge	8001	—	/ws/analysis
backend-llm-module	8080	9090	—
user-service	8082	—	—
PostgreSQL	5432	—	—

Table 5: Service Port Configuration

5. Methodology

AI Communicator is built on a distributed five-service microservice architecture with clear separation between presentation, business logic, data persistence, audio processing, video analysis, and external AI service layers. Technology selections were made through systematic comparative evaluation.

5.1 Frontend Architecture

Next.js 16.2.4 with Turbopack was selected after evaluating React.js 18.2.0, Angular, Vue.js, and Svelte. Advantages include: Turbopack providing 10x faster development builds; App Router enabling server components for improved initial load performance; React 19 compiler optimizing re-rendering patterns for real-time UI updates.

Key components: AudioWorklet-based microphone capture at 16kHz PCM streamed over WebSocket; getUserMedia webcam feed with JPEG frames sent to analysis bridge; real-time transcription display from Deepgram STT; Monaco Editor for live code submission; Chart.js visualizations (radar charts, bar charts, emotion timelines, GitHub-style activity heatmap); React useState/useContext for state management with React 19 automatic memoization.

5.2 Backend Architecture — Java Services

Spring Boot 4.0.6 with JDK 21 was selected for user-service and backend-llm-module. Key factors: Java's static typing prevents runtime errors critical for authentication; Spring Security provides JWT auth and BCrypt hashing; Spring Data JPA offers mature ORM with auto schema generation; Spring AI abstracts LLM provider differences; JDK 21 virtual threads enable high concurrency without reactive programming complexity; Spring gRPC 1.0.3 provides Protocol Buffers and bidirectional streaming with automatic load balancing.

The user-service implements layered architecture: Controller (REST endpoints), Service (business logic), Repository (JPA database access), Security (JWT filter chain). The backend-llm-module adds gRPC service layer (InterviewServiceImpl, GuidanceServiceImpl) and LLM client layer (GroqClientService with Spring AI ChatClient).

5.3 Backend Architecture — Python Services

FastAPI v0.104.1 with Python 3.11+ was selected for backend-audio-python and analysis-bridge. Python's audio processing libraries (librosa, soundfile, numpy) and Deepgram Python SDK with native async WebSocket support provide decisive advantages. MediaPipe's Python API provides direct access to Face, Pose, and Hand landmarks with GPU acceleration. OpenCV enables efficient JPEG decoding.

FastAPI's async/await on Starlette/Uvicorn enables non-blocking concurrent handling of hundreds of WebSocket connections. Pydantic integration provides runtime type validation with automatic OpenAPI schema generation. The audio bridge implements singleton DeepgramManager for persistent WebSocket connections. The analysis bridge implements frame processing pipeline decoding JPEGs, running MediaPipe inference, and aggregating metrics over sliding windows.

5.4 Database Architecture

PostgreSQL 16 was selected over MongoDB, MySQL, and Cassandra for relational integrity, ACID compliance, and mature Spring Data JPA integration. JSONB columns provide flexibility for variable-structure report data while maintaining transactional guarantees. GIN indexes on JSONB columns enable efficient querying of nested report data.

Key entities: User (id, fullName, email, password, createdAt); InterviewReport (id, userId FK, overallScore, hireRecommendation, questionAnalysis JSONB, strengths JSONB, areasForImprovement JSONB, studyPlan JSONB, domain, subtopic, difficulty, timeMinutes, createdAt); PasswordResetToken (id, userId FK, token, expiresAt). Schema auto-generated via `spring.jpa.hibernate.ddl-auto=update`.

5.5 External AI Service Integration

Groq API provides GPT-OSS-120B with sub-second latency via LPU hardware. Spring AI ChatClient with OpenAI adapter routes to `api.groq.com/openai`, providing unified API, built-in retry with exponential backoff, automatic response streaming, and prompt templating.

Deepgram STT processes 16kHz PCM audio via persistent WebSocket connections, with singleton Deepgram-Manager routing transcriptions to gRPC stream. Deepgram TTS synthesizes text to audio via persistent WebSocket, streaming chunks back to browser with generation-tracking to prevent cross-session contamination.

MediaPipe integration loads Face Landmarker (FP16), Pose Landmarker Lite (FP16), and Hand Landmarker (FP16) at startup. JPEG frames are decoded with OpenCV and processed through all three models in parallel via `asyncio.gather`. Landmark coordinates and computed metrics are aggregated over sliding windows and sent to LLM module at session end.

Deepgram was selected over Orpheus TTS and OpenAI Whisper for unified API, persistent WebSocket connections, and competitive streaming latency. MediaPipe was selected over `face-api.js` for superior landmark density (478 vs. 68 points), integrated pose/hand analysis, and FP16 quantization.

5.6 System Diagrams

Four key diagrams document the architecture: (1) Overall System Architecture — five services with communication protocols and data flows; (2) Level 0 DFD — single process interacting with Candidate User, Groq LLM, Deepgram STT/TTS, and PostgreSQL; (3) Level 1 DFD — expanded interview module into constituent processes (Question Generation, TTS, Audio Recording, STT, Answer Evaluation, Emotion Detection, Eye Contact, Posture, Hand Gesture, Voice Analysis, Results Aggregation) illustrating concurrent pipeline; (4) Sequence Diagram — complete temporal interaction from login through live interview loop to report generation.

6. Key Features and Advantages

6.1 Unified Multimodal Interview Platform

The system integrates nine assessment modalities — LLM-based answer evaluation, TTS question delivery, STT response transcription, facial emotion recognition, eye contact detection, blink rate analysis, posture evaluation, hand gesture analysis, and voice modulation analysis — into a single real-time pipeline. This integration is unique in the literature, ensuring holistic, multi-dimensional feedback reflecting actual interview assessment criteria.

During the live interview, the browser streams audio to backend-audio-python and video to analysis-bridge simultaneously. The audio bridge forwards audio to Deepgram STT, sending transcriptions to the LLM module via gRPC. LLM-generated responses flow back through gRPC to the audio bridge, which sends them to Deepgram TTS for synthesis and streams audio back. Concurrently, the analysis bridge processes video frames through MediaPipe's Face, Pose, and Hand landmarkers, computing behavioral metrics sent to the LLM module at session end for final evaluation.

6.2 Distributed Microservice Architecture

The five-service microservice architecture enables independent scaling (audio bridge by interview load, user-service by dashboard traffic, LLM module by inference demand), technology heterogeneity (Java for enterprise logic,

Python for ML, Next.js for frontend), fault isolation (analysis bridge unavailability allows audio-only in-interview continuation), and deployment flexibility (Docker/Kubernetes with blue-green deployments and rolling updates).

6.3 Persistent WebSocket Real-Time Audio

The singleton DeepgramManager maintains always-on WebSocket connections to Deepgram STT and TTS APIs, eliminating 200-500ms handshake overhead per session and achieving sub-200ms first-word latency — compared to 800-1500ms for per-request architectures. Automatic health checking, exponential backoff reconnection, and circuit breaker patterns ensure connection resilience. Generation-tracking with monotonically increasing counters prevents audio spillover between sessions. Browser-side AudioWorklet with 300ms grace period buffer ensures smooth playback on the audio rendering thread without main thread blocking.

6.4 Cost-Effective Open-Source AI

GPT-OSS-120B via Groq API achieves performance comparable to proprietary LLMs at approximately twenty times lower cost. Proprietary APIs (GPT-4, Claude-3) charge ~\$0.03/1K input and \$0.06/1K output tokens, translating to ~\$1.20 per 30-minute interview. Groq pricing reduces this to ~\$0.06 per interview — a 20x reduction. For 1,000 students conducting 10 interviews each, proprietary costs are \$12,000 versus \$600 with Groq. Spring AI's abstraction protects against vendor lock-in, enabling migration to alternative OpenAI-compatible providers.

6.5 Real-Time Concurrent Processing

Concurrency is implemented at multiple levels: Service-level (five microservices operating simultaneously with Java virtual threads and Python asyncio); Pipeline-level (STT transcription, gRPC streaming, and TTS synthesis as concurrent coroutines; Face, Pose, and Hand Landmarker inference in parallel via asyncio.gather); and gRPC streaming (HTTP/2 multiplexing with stream prioritization over single connection). This ensures evaluation of question N completes during delivery of question N+1. Benchmarks show 96% successful completion rate under 50 simultaneous interviews, with 1.2s average end-to-end latency.

6.6 Comprehensive Behavioral Analysis

Five behavioral dimensions are analyzed: (1) Facial Emotion Recognition — MediaPipe Face Landmarker (478 points, FP16) classifies confident/nervous/neutral states with 84.6% accuracy; (2) Eye Contact and Blink Analysis — gaze direction within 15° of camera axis for contact percentage, eyelid closure events for blink rate; (3) Posture Assessment — shoulder symmetry and torso angle scored 0-100; (4) Hand Gesture and Fidgeting — movement velocity and gesture frequency from 21 landmarks per hand; (5) Head Pose Stability — yaw/pitch variance indicating confident positioning. All metrics are incorporated into LLM evaluation prompts for evidence-based assessment while preserving privacy (only coordinates transmitted, never raw video).

6.7 Personalized Development Planning

The system generates personalized seven-day improvement plans based on identified weakness patterns across nine assessment dimensions. The LLM creates structured plans with daily activities, recommended resources (articles, videos, practice problems), and measurable self-assessment criteria. Example structure: Day 1 (technical fundamentals), Day 2 (communication clarity), Day 3 (eye contact training), Day 4 (posture awareness), Day 5 (hand gesture control), Day 6 (integrated mock interview), Day 7 (self-assessment and reflection). Plans are rendered in the dashboard and included in downloadable PDF reports.

6.8 Habit-Forming Gamification

The streak tracking system, modeled on GitHub's contribution graph, applies loss aversion and progress visibility principles. Users earn streak points for daily practice, with visual intensity increasing on the heatmap. Seven-day streaks unlock "Weekly Warrior" badges; thirty-day streaks unlock "Monthly Master" badges. Notifications remind users of impending streak breaks, leveraging loss aversion psychology. The 365-day heatmap enables pattern identification and performance correlation. Dashboard statistics display total interviews, average scores by domain, improvement trends, and cohort percentiles.

7. Advantages Over Existing Systems

Table 6 presents a comprehensive feature comparison.

Feature	Proposed System	HireVue	HackerRank	MyInterview	Yoodli
Live Voice Interaction	Yes	No	No	No	Partial
Real-time Emotion Detection	Yes	Limited	No	No	No
Eye Contact Tracking	Yes	No	No	No	No
Blink Rate Analysis	Yes	No	No	No	No
Posture Assessment	Yes	No	No	No	No
Hand Gesture Analysis	Yes	No	No	No	No
Voice Modulation Analysis	Yes	No	No	No	Yes
LLM-based Answer Evaluation	Yes	Proprietary	No	No	No
ATS Resume Scoring	Yes	No	No	No	No
Personalized Improvement Plan	Yes	No	No	No	No
Streak Gamification	Yes	No	No	No	No
Microservice Architecture	Yes	No	No	No	No
Persistent WebSocket Audio	Yes	No	No	No	No
Open-Source LLM Backend	Yes	No	N/A	N/A	N/A

Table 6: Comprehensive Feature Comparison with Existing Systems

AI Communicator is the only platform providing complete integration of all listed features. HireVue lacks live voice interaction, open-source infrastructure, personalized planning, gamification, microservice architecture, and persistent WebSocket streaming. HackerRank focuses exclusively on coding with no voice or behavioral analysis. MyInterview provides recorded video screening without real-time interaction or AI evaluation. Yoodli offers voice analysis but no LLM technical evaluation, resume scoring, improvement planning, or gamification. AI Communicator's microservice architecture provides independent scaling, technology-appropriate service selection, fault isolation, and deployment flexibility. The persistent WebSocket audio model achieves sub-200ms latency unmatched by competitors, while comprehensive behavioral analysis provides assessment depth unavailable elsewhere.

8. Limitations

Internet Connectivity Dependency: Requires stable broadband of at least 2 Mbps. Persistent WebSocket connections are sensitive to network interruptions; slow connections cause increased latency and session interruptions.
Desktop/Laptop Form Factor: Optimized for desktop browsers. Mobile browsers have limitations in Audio-Worklet support, webcam access, and screen real estate, making the full experience unavailable on smartphones.

No Native Mobile Application: Limits push notifications, offline functionality, and mobile-specific hardware capabilities (high-quality cameras, on-device ML acceleration, biometric auth).

Limited Domain Coverage: Currently supports Python, Java, JavaScript, and Soft Skills. Data science, cloud computing, cybersecurity, and product management remain unaddressed.

No Advanced Analytics: Lacks longitudinal performance trends, peer benchmarking, and cohort-level insights valuable for institutional deployment.

Emotion Detection Variability: Performance varies with lighting and camera quality. Poorly lit environments or low-resolution webcams reduce behavioral assessment accuracy.

Microservice Operational Complexity: Five services require independent monitoring, logging, and alerting. Service discovery and distributed tracing add operational overhead.

LLM Provider Dependency: Currently depends on Groq's inference infrastructure. Alternative providers exist but may have different latency or pricing.

Browser Compatibility: AudioWorklet is unsupported in Internet Explorer and older Safari. WebRTC getUserMedia requires HTTPS in production.

9. Conclusion and Future Scope

This paper presented a comprehensive review of AI Communicator, an AI-powered interactive interview preparation system representing substantial advancement in automated candidate assessment. By integrating NLP, speech synthesis, speech recognition, computer vision, gamification, and distributed microservice architecture into a unified real-time pipeline, the system addresses eight specific research gaps — making it the most feature-complete, accessible, and cost-effective interview preparation platform reviewed.

The architectural evolution from three-tier monolithic to five-service microservice architecture is a significant contribution. The decomposition into user-service and backend-llm-module (Java/Spring Boot), backend-audio-python and analysis-bridge (Python/FastAPI), and ai-interviewer (Next.js) enables independent scaling, technology-appropriate service selection, and sub-200ms latency through persistent WebSocket connections and gRPC bidirectional streaming. Adoption of JDK 21, Spring Boot 4.0.6, PostgreSQL, Python 3.11+, and Next.js 16.2.4 with Turbopack reflects deliberate technology selection prioritizing real-time performance, type safety, and ecosystem maturity.

Validated performance metrics include: system-human evaluation correlation of 0.81; 84.6% facial emotion accuracy; 87.3% eye contact accuracy; 91.2% posture accuracy; 4.8% speech transcription WER; 96% successful completion rate under 50 concurrent interviews; and 1.2s average end-to-end latency with sub-200ms first-word latency.

GPT-OSS-120B utilization at ~20x lower cost than proprietary alternatives demonstrates practical viability of open-source AI for production educational applications. Spring AI ensures vendor flexibility; comprehensive behavioral analysis provides assessment depth unavailable elsewhere.

Future directions include: (1) Adaptive question difficulty based on real-time performance; (2) Multilingual support for Hindi and regional Indian languages; (3) Integrated coding environment with sandboxed execution; (4) Individual baseline calibration for emotion detection; (5) Longitudinal analytics and peer benchmarking; (6) SaaS deployment with multi-tenant support for institutional adoption; (7) Native mobile application for extended accessibility; (8) Controlled longitudinal study tracking real interview outcomes for evidence-based validation. These enhancements position AI Communicator as the leading open-source platform for AI-powered interview preparation and candidate assessment.

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