PROPOSAL OF PERSONAL PROJECT MULTIMODAL VIRTUAL COMMUNICATE SYSTEM

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Abstract

This project proposes the design and development of a **Multimodal Virtual Communication System** that integrates facial expression recognition, acoustic-phonological modeling, speech generation, and personality reconstruction into a unified framework for naturalistic human–machine interaction. The system aims to analyze a user's emotional state through **Facial Expression Recognition (FER)**, capture speaker individuality and prosodic features via **voiceprint and prosody modeling**, and generate expressive speech that preserves both timbre and intonation. Beyond signal-level modeling, the project explores the reconstruction of **personality traits and interaction style**, enabling dialogue agents to simulate consistent personas.

Methodologically, the project employs **knowledge distillation** and **margin-based embedding losses** to build a robust FER backbone, **few-shot adaptation** and **generative phonology models** to capture prosody under limited data conditions, and **zero-/few-shot text-to-speech architectures** to synthesize natural speech. A **persona-conditioned dialogue module** is further introduced to approximate interaction style, while **transformer-based multimodal fusion** integrates visual, acoustic, and linguistic cues in real time.

The expected outcomes include: (i) a validated FER model robust under stress conditions, (ii) a voiceprint–prosody module capable of low-resource adaptation, (iii) an expressive speech generation system, (iv) a prototype persona simulation module, and (v) an integrated multimodal communication system. Potential applications span **personal companionship, healthcare support, language learning, and remembrance technologies**. By addressing both technical feasibility and human-centered design, this project contributes to the advancement of **affective computing** and the long-term vision of emotionally meaningful virtual communication.

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INTRODUCTION

Overview

Human communication is inherently multi-modal, involving not only spoken language but also facial expressions, prosody, and subtle paralinguistic cues. Recent advances in machine learning and affective computing have enabled increasingly accurate recognition of these modalities in isolation. However, the integration of visual, acoustic, and linguistic signals into a coherent, interactive system remains an open research challenge.

This project envisions the development of a Virtual Human Communication System capable of simulating and preserving human-like interaction across multiple channels: voice, dialogue, facial expression, appearance, personality, and conversational style. Such a system has potential applications in remembrance and companionship (providing a means of continued interaction with departed loved ones), healthcare and therapy (offering emotional support or speech rehabilitation), and self-reflection (enabling individuals to engage in dialogue with a virtual representation of themselves).

The proposed research Is structured as a multi-stage roadmap. The first stage, represented by the current Final Year Project (FYP), focuses on Facial Expression Recognition (FER) as a foundational module. The second stage extends into acoustic-phonological modeling, particularly vowel length contrasts and prosodic features, to capture the temporal and expressive dimensions of speech. The final stage aims to integrate these components into a unified multi-modal framework, enabling real-time, naturalistic interaction.

By progressively building from robust unimodal modules towards multi-modal integration, this research seeks to establish both the technical feasibility and the conceptual significance of virtual human communication systems. Beyond technical contributions, the project also addresses broader questions of trust, ethics, and human meaning, recognizing that such systems intersect deeply with emotional and social dimensions of human life.

Motivation

Human communication is not limited to words alone; it is a rich interplay of facial expressions, voice, prosody, and conversational style. While recent advances in machine learning have enabled progress in each of these modalities, existing systems remain fragmented and task-specific. The motivation for this study arises from both academic curiosity and personal vision: to build a foundation for a Virtual Human Communication System that can support naturalistic, emotionally meaningful interaction.

From an academic perspective, the motivation lies in addressing critical gaps in current research. Facial Expression Recognition (FER) models, despite achieving high benchmark accuracy, often fail under real-world conditions such as class imbalance, image degradation, and deployment drift. Similarly, acoustic-phonological modeling has yet to fully capture expressive features such as vowel length contrasts, prosody, and speaker individuality. By systematically strengthening these unimodal backbones and exploring their integration, this project aims to contribute to the emerging field of multi-modal affective computing.

From a societal perspective, the motivation is grounded in the potential applications of such a system. A virtual communication agent capable of simulating voice, expression, and personality could:

- Provide comfort and remembrance, enabling continued interaction with departed loved ones.

- Support healthcare and therapy, offering companionship, speech rehabilitation, and emotional support.

- Facilitate self-reflection, allowing individuals to engage in dialogue with a “virtual self” for decision-making and personal growth.

From a personal perspective, this project represents the first step in a long-term research journey. The current FYP on FER establishes the visual backbone; subsequent work on acoustic-phonological modeling will extend into the auditory domain. Together, these stages form the foundation for a future system that is not only technically robust but also emotionally resonant.

In sum, the motivation for this study is to bridge the gap between technical feasibility and human meaning, laying the groundwork for communication systems that are academically rigorous, practically useful, and deeply human-centered.

Background

Human communication is inherently multi-modal, combining verbal content with non-verbal cues such as facial expressions, prosody, and gesture. In recent decades, advances in affective computing and speech technology have enabled researchers to model these modalities separately with increasing accuracy.

In the visual domain, Facial Expression Recognition (FER) has become a central task for understanding human affect. Convolutional Neural Networks (CNNs) and, more recently, Vision Transformers (ViTs) have demonstrated strong performance on benchmark datasets such as AffectNet and RAF-DB. However, FER systems remain vulnerable to class imbalance, image quality degradation, and deployment drift, which limit their reliability in real-world applications.

In the acoustic domain, phonological contrasts such as vowel length and prosodic features like intonation and rhythm play a crucial role in conveying meaning and emotion. Deep learning approaches, including Generative Adversarial Networks

(GANs) and sequence models, have been applied to capture these fine-grained temporal patterns. Yet, challenges remain in modeling cross-linguistic variation, speaker individuality, and expressive nuance.

Despite progress in unimodal research, the integration of visual and acoustic signals into a unified system for naturalistic interaction is still underexplored. Existing multi-modal systems often focus on task-specific objectives (e.g., emotion classification or speech recognition) rather than holistic communication. Moreover, ethical considerations such as trust, authenticity, and potential misuse (e.g., deepfakes) highlight the importance of developing systems that are not only technically robust but also socially responsible.

This background motivates a staged research program: beginning with robust FER as a foundation, extending into acoustic-phonological modeling, and ultimately aiming towards a Virtual Human Communication System capable of supporting meaningful, real-time interaction.

Problem Statements

Although significant progress has been made in unimodal affective computing, current systems remain fragmented and limited in their ability to support naturalistic, multi-modal human communication. Facial Expression Recognition (FER) models, while achieving high accuracy on benchmark datasets, often fail under real-world conditions such as class imbalance, image quality degradation, and deployment drift. These weaknesses undermine their reliability as foundational components for interactive systems.

Similarly, in the acoustic domain, deep learning methods have advanced the modeling of phonological contrasts and prosodic features, yet challenges persist in capturing speaker individuality, cross-linguistic variation, and expressive nuance. Existing approaches tend to optimize narrowly for classification or generation tasks, without addressing how these acoustic features can be integrated into broader communicative contexts.

Most critically, there is a lack of research that integrates visual and acoustic modalities into a unified framework capable of sustaining real-time, meaningful interaction. Current multi-modal systems are typically task-specific (e.g., emotion classification, speech recognition) and do not address the higher-level goal of simulating human-like dialogue and presence. Furthermore, issues of calibration, trust, and ethical use remain underexplored, raising concerns about the deployment of such systems in sensitive domains such as healthcare or remembrance.

Therefore, the central problem this project addresses is:

- How can we design and evaluate robust unimodal modules (FER and acoustic-phonological modeling) that can withstand real-world weaknesses, and progressively integrate them into a multi-modal system capable of supporting naturalistic, trustworthy, and emotionally meaningful human-machine communication?

Research Objectives

The overarching objective of this research is to establish a progressive roadmap towards a Virtual Human Communication System by first developing robust unimodal modules and then exploring their integration into a multi-modal framework. Specifically, the project seeks to:

1. Develop a reliable Facial Expression Recognition (FER) backbone

- Train and evaluate teacher–student architectures (e.g., CNNs, ViTs) using knowledge distillation (KD/DKD).

- Conduct systematic stress tests (class imbalance, image quality degradation, deployment drift) to identify system weaknesses and calibration issues.

2. Advance acoustic-phonological modeling for expressive speech

- Investigate deep learning approaches (e.g., GANs, duration models) to capture vowel length contrasts, prosodic variation, and speaker individuality.

- Build an acoustic backbone that complements FER by modeling voice, intonation, and rhythm.

3. Explore pathways for multi-modal integration

- Examine strategies for combining visual (FER) and acoustic (phonological) channels with dialogue models to support naturalistic interaction.

- Evaluate the feasibility of persona conditioning (tone, style, personality) for generating coherent, human-like responses.

4. Address trust, calibration, and ethical considerations

- Assess the reliability of the system under real-world deployment conditions.

- Identify risks of misuse (e.g., deepfakes) and propose safeguards to ensure socially responsible applications.

By achieving these objectives, the project aims to lay the groundwork for a multi-modal, trustworthy, and emotionally meaningful communication system, with potential applications in remembrance, healthcare, and self-reflection.

Related Work

Research on human communication technologies spans multiple domains, including facial expression recognition (FER), acoustic-phonological modeling, and multi-modal integration. This section reviews key contributions and limitations in each area.

Facial Expression Recognition (FER)

Early FER systems relied on handcrafted features such as Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). With the advent of deep learning, Convolutional Neural Networks (CNNs) (e.g., ResNet, EfficientNet) and more recently Vision Transformers (ViTs) have achieved state-of-the-art performance on large-scale datasets such as AffectNet and RAF-DB.

- Strengths: High accuracy under controlled conditions; effective feature extraction.

- Limitations: Performance degrades under class imbalance, occlusion, low resolution, and domain shift. Calibration issues also reduce trustworthiness in deployment.

Recent work has explored knowledge distillation (KD) and data augmentation to improve robustness, but systematic stress testing remains underexplored.

Acoustic-Phonological Modeling

In the speech domain, deep learning has advanced the modeling of phonological contrasts and prosodic features. Studies on vowel length contrasts highlight their importance in distinguishing meaning across languages (e.g., Japanese, Finnish, Arabic).

- Approaches: Generative Adversarial Networks (GANs), recurrent neural networks (RNNs), and transformer-based models have been applied to capture duration, rhythm, and intonation.

- Challenges: Capturing speaker individuality, cross-linguistic variation, and expressive nuance remains difficult. Most models optimize for recognition or synthesis, rather than integration into interactive systems.

Multi-Modal Affective Computing

Multi-modal systems aim to combine visual, acoustic, and linguistic cues for richer affective understanding. Recent work has applied fusion strategies (early, late, and hybrid fusion) to tasks such as emotion recognition and sentiment analysis.

- Strengths: Improved accuracy compared to unimodal systems; ability to capture complementary signals.

- Limitations: Many systems are task-specific (e.g., classification) and do not support real-time, naturalistic interaction. Moreover, issues of calibration, latency, and ethical use (e.g., deepfake risks) are often overlooked.

Gaps in the Literature

- Lack of robust FER backbones validated under real-world stress conditions.

- Limited exploration of acoustic-phonological modeling for expressive, cross-linguistic communication.

- Insufficient research on multi-modal integration aimed at holistic, trustworthy, and interactive communication systems.

Significance of the Study

This study is significant on multiple levels, spanning both academic contributions and broader societal impact.

Academic Contributions

- Advancing robustness in FER: By systematically stress-testing teacher–student architectures under imbalance, quality degradation, and deployment drift, the project contributes new insights into the reliability and calibration of FER systems beyond benchmark accuracy.

- Extending acoustic-phonological modeling: The focus on vowel length contrasts and prosodic features addresses a relatively underexplored area in deep learning, bridging phonology and machine learning. This work has the potential to enrich the field of speech technology with models that capture expressive and cross-linguistic variation.

- Towards multi-modal integration: By framing FER and acoustic modeling as complementary backbones, the study lays the groundwork for future research in multi-modal affective computing, moving beyond task-specific objectives towards holistic communication systems.

Practical and Societal Relevance

- Remembrance and companionship: The envisioned system could provide a means of preserving interaction with departed loved ones, offering comfort and continuity in the face of loss.

- Healthcare and therapy: Virtual companions with reliable emotion recognition and expressive speech capabilities could support mental health interventions, elderly care, and speech rehabilitation.

- Self-reflection and personal growth: A system capable of simulating dialogue with a “virtual self” could serve as a tool for reflection, decision-making, and emotional regulation.

Ethical and Humanistic Dimensions

- The project acknowledges the ethical challenges of building systems that simulate human presence, including risks of misuse (e.g., deepfakes) and issues of authenticity. By explicitly incorporating calibration, trust, and responsible deployment into the research objectives, the study contributes to the development of socially responsible affective technologies.

In sum, the significance of this study lies not only in its technical contributions to FER and acoustic modeling, but also in its potential to shape the future of human-machine communication in ways that are academically rigorous, practically useful, and emotionally meaningful.

Literature Review

1. Facial Expression Recognition (FER)

Facial expression recognition (FER) has evolved from handcrafted features to deep learning backbones. Convolutional Neural Networks (CNNs) such as ResNet and EfficientNet have demonstrated strong performance, while Vision Transformers (ViTs) offer competitive accuracy with lightweight architectures. Knowledge Distillation (KD) has become a key strategy for compressing large teacher ensembles into efficient student models. Hinton et al. [1] first introduced KD, followed by Born-Again Networks (BAN) [2], which showed the regularization effect of iterative self-distillation. Zhao et al. [3] proposed Decoupled KD (DKD), mitigating gradient suppression for confusable classes. Embedding losses such as ArcFace [4] enhance inter-class separation, while EfficientNet [5] provides superior accuracy–efficiency trade-offs. Recent works [6]–[8] extend KD with feature-only distillation, grouped KD, and adaptive scheduling, addressing robustness under imbalance and domain drift.

2. Acoustic-Phonological Modeling

Phonological contrasts such as vowel length and prosody are central to expressive speech. Beguš [9], [10] demonstrated that GANs can learn allophonic alternations and phonological features in an unsupervised manner. Extensions such as fiwGAN [11] capture vowel harmony and featural structures. Prosody modeling has advanced with discourse-scale approaches, such as ProsodyGAN [12] and ProMode [13], which disentangle pitch, energy, and duration for expressive synthesis. Speaker embeddings (x-vectors, ECAPA-TDNN) remain essential for capturing individuality, though disentangling identity from prosody under low-resource conditions remains challenging.

3. Speech Generation

Zero- and few-shot text-to-speech (TTS) systems enable cloning of unseen speakers with limited data. Kim et al. [14] introduced P-Flow, a flow-matching model for fast zero-shot TTS. Liu et al. [15] proposed DifGAN-ZSTTS, combining FastSpeech2 with diffusion decoders to improve similarity for unseen speakers. DiFlow-TTS [16] factorizes prosody and acoustic tokens for low-latency generation. Multilingual systems such as YourTTS [17], XTTS [18], and BnTTS [19] extend few-shot adaptation to low-resource languages. Hierarchical prosody modeling [20] further enhances expressiveness.

4. Personality Reconstruction

Persona-conditioned dialogue has been studied through datasets such as PersonaChat [21] and MSC [22]. Su et al. [23] augmented personas with Big Five traits, improving consistency via reranking. Cho et al. [24] modeled implicit user personas with conditional variational inference, while Hsu et al. [25] introduced discourse-coherent personalization using graph encoders. These works highlight the feasibility of simulating conversational style, though authenticity and ethical concerns remain unresolved.

5. System Integration

Multimodal affective computing integrates vision, audio, and text. Transformer-based fusion has become dominant, as demonstrated by Zhang et al. [26] in the ABAW challenge, and Deng et al. [27] with dense fusion transformers. Mohamed et al. [28] proposed context-aware fusion, while Tagmatova et al. [29] emphasized robustness under occlusion and low light. Surveys [30], [31] highlight the promise of multimodal affective computing, while noting challenges in synchronization, latency, and calibration

Methodology

1. Facial Expression Recognition (FER) – Emotion Analysis Module

Objective: To establish a robust FER backbone capable of accurately recognizing emotions under real-world conditions.

Approach:

- **Model architecture:** Employ ResNet18, EfficientNet-B3, and ConvNeXt as teacher ensemble models; distill knowledge into a lightweight ViT-Tiny student.
- **Knowledge Distillation pipeline:** Apply staged distillation (Hinton KD → Born-Again Networks (BAN) → Decoupled KD (DKD)) to enhance student performance and generalization.
- **Embedding loss:** Integrate ArcFace margin loss to increase inter-class separation, particularly for subtle expressions (e.g., fear vs. disgust).
- **Stress testing:** Conduct systematic evaluations under class imbalance, low-quality images, and domain drift to generate a failure map.

Evaluation:

- Accuracy (top-1, F1-score)
- Calibration metrics (Expected Calibration Error, Brier score)
- Robustness under stress scenarios

2. Acoustic-Phonological Modeling – Voiceprint and Prosody Module

Objective: To capture speaker individuality and prosodic features (pitch, energy, duration) for expressive voice reconstruction.

Approach:

- **Speaker embedding:** Extract identity features using x-vector and ECAPA-TDNN architectures.
- **Prosody modeling:** Develop a prosody encoder to capture pitch contours, energy profiles, and duration patterns.
- **Generative modeling:** Apply GAN-based phonology modeling (e.g., Beguš, fiwGAN) to simulate vowel length contrasts and cross-linguistic prosody.
- **Few-shot adaptation:** Utilize parameter-efficient fine-tuning (LoRA, adapters) to adapt models with limited user data.
- **Data augmentation:** Employ pitch shifting, time-stretching, and noise injection to improve robustness in low-resource conditions.

Evaluation:

- Speaker similarity (cosine similarity of embeddings, ABX test)
- Prosody accuracy (pitch correlation, duration error)
- Naturalness (Mean Opinion Score, MOS)

3. Speech Generation – Expressive TTS Module

Objective: To generate natural speech that preserves both speaker identity and expressive prosody.

Approach:

- **Backbone models:** Use FastSpeech 2 and VITS as baseline TTS systems; explore flow/diffusion-based models (P-Flow, DifGAN-ZSTTS, DiFlow-TTS) for reduced latency.
- **Zero-/few-shot cloning:** Adapt multilingual pre-trained TTS models (e.g., YourTTS, XTTS) with minimal user data.
- **Prosody factorization:** Separate timbre tokens (speaker identity) from prosody tokens (intonation, rhythm) for controllable synthesis.

Evaluation:

- MOS for naturalness
- Speaker similarity (subjective evaluation + embedding-based metrics)
- Prosody transfer accuracy

4. Personality Reconstruction – Persona Module (Most Challenging)

Objective: To simulate an individual's interaction style and personality traits.

Approach:

- **Persona-conditioned dialogue:** Use a large language model (LLM) as the conversational backbone, conditioned on persona embeddings (tone, style, lexical choice).
- **Trait augmentation:** Incorporate Big Five personality traits as conditioning signals.
- **Implicit persona detection:** Apply variational inference to infer user persona from dialogue history.
- **Discourse coherence:** Employ graph-based encoders to maintain multi-turn coherence.

Evaluation:

- Consistency metrics (persona adherence, trait alignment)
- Human evaluation (naturalness, authenticity, trust)
- Ethical review (consent, misuse risk)

5. System Integration – Multimodal Communication System

Objective: To integrate FER, voiceprint/prosody modeling, speech generation, and personality simulation into a real-time multimodal communication system.

Approach:

- **Fusion strategies:** Implement transformer-based cross-attention (early/late/hybrid fusion) to combine visual, acoustic, and linguistic embeddings.
- **Dialogue agent:** Use an LLM-based conversational core that dynamically adjusts responses based on FER and prosody inputs.

- **Real-time pipeline:** Apply model compression and streaming inference to ensure low-latency interaction.

Evaluation:

- System latency (milliseconds per response)
- User study (perceived naturalness, emotional appropriateness, companionship value)
- Robustness under real-world deployment

Future Challenges: Personality Reconstruction

While facial expression recognition and acoustic-phonological modeling provide the technical backbone for simulating human affect, the reconstruction of personality remains the most difficult and open challenge. Unlike expressions or prosodic features, personality is not a single observable signal but an emergent property of linguistic choices, prosodic tendencies, emotional responses, and interactional style.

Key challenges include:

- Data scarcity: Ordinary users rarely possess large datasets of a person's speech, video, or behavioral logs. Methods must therefore operate under few-shot or low-resource conditions, learning from limited samples.

- Multi-modal fusion: Personality is expressed across modalities (voice, facial expression, lexical choice). Capturing consistent traits requires cross-modal alignment rather than unimodal modeling.

- Authenticity vs. simulation: Even if a system can approximate a persona, it raises the question of whether this constitutes the "real" personality or merely a configurable simulation.

- Ethical considerations: Personality reconstruction intersects with issues of consent, memory, and identity. Safeguards are necessary to prevent misuse (e.g., unauthorized replication).

Despite these challenges, progress in few-shot learning, generative modeling, and persona-conditioned dialogue systems suggests that partial reconstruction is feasible. The long-term vision is to enable systems that can adaptively simulate interaction styles, providing applications in personal companionship, healthcare support, and remembrance technologies.

Project Plan

1. Objectives Recap

- Develop a robust **Facial Expression Recognition (FER)** backbone with knowledge distillation and stress testing.
- Build an **Acoustic-Phonological Modeling** module to capture speaker identity and prosody under few-shot conditions.
- Implement **Speech Generation** that preserves both timbre and expressive prosody.
- Explore **Personality Reconstruction** through persona-conditioned dialogue.
- Integrate all modules into a **Multimodal Communication System** for real-time interaction.

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2. Project Schedule and Milestones

Phase	**Timeline**	**Key Activities**	**Deliverables / Milestones**
Phase 1: Literature Review & Design	Month 1–2	- Conduct in-depth literature review on FER, KD, prosody modeling, TTS, persona dialogue, multimodal fusion. - Define datasets and evaluation metrics. - Finalize system architecture.	**Milestone 1:** Completed literature review chapter and finalized methodology design.

Phase	**Timeline**	**Key Activities**	**Deliverables / Milestones**
Phase 2: FER Module Development	Month 2–3	- Train teacher ensemble (ResNet18, EfficientNet-B3, ConvNeXt). - Apply staged KD (KD → BAN → DKD) into ViT-Tiny student. - Conduct stress testing (imbalance, low-quality, domain drift).	**Milestone 2:** Robust FER backbone with evaluation report.
Phase 3: Acoustic-Phonological Modeling	Month 3–4	- Implement speaker embedding (x-vector, ECAPA-TDNN). - Build prosody encoder (pitch, energy, duration). - Experiment with GAN-based phonology modeling. - Apply few-shot adaptation with limited data.	**Milestone 3:** Prototype voiceprint + prosody module with evaluation results.
Phase 4: Speech Generation	Month 4–5	- Integrate FastSpeech 2 / VITS baseline. - Explore flow/diffusion-based models (P-Flow, DifGAN-ZSTTS, DiFlow-TTS). - Implement prosody factorization. - Evaluate naturalness, similarity, prosody accuracy.	**Milestone 4:** Expressive TTS system with preliminary user evaluation.

Phase	**Timeline**	**Key Activities**	**Deliverables / Milestones**
Phase 5: Personality Reconstruction	Month 5–6	- Implement persona-conditioned dialogue with LLM. - Add Big Five trait conditioning. - Explore implicit persona detection and discourse coherence.	**Milestone 5:** Persona simulation module with evaluation on consistency and authenticity.
Phase 6: System Integration	Month 6–7	- Fuse FER, prosody, TTS, and persona modules. - Implement transformer-based multimodal fusion. - Optimize for real-time performance.	**Milestone 6:** Integrated multimodal prototype.
Phase 7: Testing & Evaluation	Month 7–8	- Conduct user studies (naturalness, emotional appropriateness, companionship value). - Measure latency and robustness in real-world scenarios. - Ethical review and risk assessment.	**Milestone 7:** Final evaluation report and user study results.
Phase 8: Documentation & Final Submission	Month 8–9	- Write final thesis/report. - Prepare presentation and defense materials.	**Milestone 8:** Completed thesis and project defense.

3. Risk Management

- **Data scarcity:** Mitigated by few-shot learning and augmentation.
- **Latency issues:** Addressed with model compression and non-autoregressive architectures.
- **Ethical concerns:** Explicitly include consent, identity protection, and misuse prevention in evaluation.

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4. Expected Outcomes

- A validated FER backbone robust under stress conditions.
- A voiceprint + prosody module capable of few-shot adaptation.
- An expressive TTS system with controllable prosody.
- A persona-conditioned dialogue agent simulating interaction style.
- An integrated multimodal system demonstrating real-time virtual human communication.

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