I Understand Understand You: A Reliable Multi-Agent Facilitator for Reducing Communication Breakdowns

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***Abstract*—Imagine a mediator who fosters active listening and effective communication between English speakers, without judgment, but by encouraging each party involved to be themselves. Imagine that this speaker not only hears you, but "understands understands" you! Picture that conversations between English-speaking professionals from across the globe can be possible and seamless, and all the while, without any form of prejudice! Think about it, for a moment, that there would no longer be any need for code-switching! This is why *I Understand Understand You (IUUY)*, an active-listening facilitator and a coach that helps promote multi-culturally competent conversations, might just be the answer you have been waiting for. *IUUY*, though still in its early research and development stages, is a multi-agent AI system (MAS) augmented by blockchain technology to facilitate great conversations and reduce communication breakdowns, both ethically and securely. Currently a 4-agent entity, it aims to foster fair, inclusive, and trustworthy conversations in culturally diverse professional and personal spaces. An Agile methodology, particularly the Scrum framework, will guide its continuous iterative development, user-centric prototyping, and responsive learning cycles.**

***Index Terms*—Active Listening, Code-switching, Blockchain, Collaboration, Dialtectal Variation, MAS,**

I. Introduction

Although English has become the dominant language of international business and economic transactions, its dialectal diversity is extensive, and these variations pose real risks for miscommunication in culturally diverse teams [1]. Studies show communication breakdowns frequently hinder effective coordination in diverse environments, especially during high-stakes or time-sensitive situations [2]–[4]. Fiset et al. [5] show that "language-related misunderstanding," encompassing non-native accents, code-switching, and jargon, significantly undermines both employee performance and attitudes at work. Similarly, according to a June 9, 2021 *Harvard Business Review* [6], a survey of 90 countries found that nearly 90 percent of knowledge workers collaborate virtually across borders; yet, dialectal differences within English remain a persistent barrier to smooth interaction [7].

When dialectal mismatches occur, the human cost can be high: reduced efficiency, decreased inclusivity, and ultimately lower job satisfaction and higher turnover. A recent industry report found that 41 percent of professionals directly attribute productivity losses to poor communication, while 35 percent report decreased job satisfaction as a consequence of miscommunication. Beyond statistics, qualitative studies show that subtle misunderstandings—over nuances of syntax or prosody can erode trust and collaborative cohesion in ways that conventional meeting transcripts fail to document [8].

One coping mechanism is code-switching. This happens when bilingual or multilingual speakers adjust dialect, tone, or even entire grammatical constructions to align with perceived norms. But this strategy carries its own toll. Liu et al. demonstrate that increased cognitive load directly suppresses intra-clausal code-switching, suggesting that maintaining multiple dialectal frames simultaneously is mentally taxing [9]. Furthermore, a 2025 *Frontiers* review of cognitive-control frameworks finds that sustained code-switching triggers measurable fatigue, identity tension/crisis, and emotional exhaustion, outcomes linked to impostor syndrome and burnout in corporate settings.

Meanwhile, today's leading affective-computing tools (e.g., speech emotion analyzers and automatic meeting summarizers as seen in tools like *Read AI*) fall short on two fronts. First, they are predominantly trained on Western-centric datasets, embedding cultural biases that misinterpret non-Western speech patterns [10]. Second, they operate post-hoc, producing summaries after the fact, depriving users of real-time corrective feedback when misunderstandings might be averted most effectively.

Taken together, these findings point to an urgent need for a system that:

1) **Respects dialectal variation/diversity** without enforcing a "standard" English norm,
2) **Reduces communication breakdown and improves clarity** by identifying and highlighting ambiguous statements in real-time,
3) **Fosters authentic engagement and active listening** by clarifying intent rather than correcting form,
4) **Operates in real time** to proactively identify and correct discrepancies before they escalate.

The proposed *I Understand Understand You* (*IUUY*) multi-agent AI system addresses key limitations in current language technologies by focusing not on standardizing speech but on interpreting ambiguity, actively checking for understanding, and preserving the richness of each speaker's dialect in post-meeting notes. Embedded within virtual meeting platforms and refined through iterative, Scrum-based development, *IUUY* aims to redefine how global teams navigate dialectal variation in communication. The name *IUUY* draws from both linguistic nuance and cultural pragmatics. In American English, the repetition in *"I understand understand you"* is an uncommon but deliberate rhetorical emphasis, akin to bolding a word for clarity and empathy. In Nigerian English, repetition is a familiar and expressive linguistic strategy used to show sincerity and depth of understanding. Thus, *IUUY* is not just a name, but a conceptual anchor for a system that values not only what is said, but how deeply it is received and recognized across dialectal boundaries.

II. Background and Related Works

Current technological approaches to inclusive communication in multicultural environments remain constrained by three interrelated limitations: a predominant reliance on Western, Educated, Industrialized, Rich, and Democratic (WEIRD) datasets that inadequately represent global linguistic and cultural diversity [11]. This tendency focuses on retrospective or monolingual processing rather than enabling real-time, dialect-aware mediation, and a fragmented treatment of Artificial intelligence (AI) and blockchain technologies that lacks unified, multi-agent coordination. This review harmonizes recent developments across these domains and motivates the need for the proposed *IUUY* system.

A. *Dialectal Variation in English*

Sociolinguistic scholarship has richly documented the phonetic, lexical, and grammatical features that distinguish world English dialects, including Nigerian, Indian, Korean, British, American, and other varieties [12]. However, these descriptive studies rarely translate into Automatic Speech Recognition (ASR) or Natural Language Understanding (NLU) models that can reliably recognize and interpret "non-standard" dialects in real-time. As a result, most commercial speech systems still underperform on utterances exhibiting characteristic monophthongization, lexical innovations, or semantic shifts found in non-WEIRD dialects, leaving speakers of these varieties underserved.

B. *Code-Switching and its Sociocognitive Effects*

Empirical work shows that bilinguals and multilinguals engage in intra- and inter-clausal code-switching as a communicative strategy, but that increased cognitive load suppresses such switches, particularly within clauses, highlighting the mental toll of juggling dialectal frames [9]. Moreover, systematic reviews underline a lack of uniformity in experimental methods for studying code-switching and a shortage of technological tools to support code-switchers in real-world settings, forcing speakers to either assimilate or risk fatigue and alienation.

C. *Communication in Multicultural Teams*

Research in organizational psychology reveals that linguistic diversity impedes group cohesion, decision-making, and knowledge sharing. Language mismatches can induce social fragmentation, reduce rhetorical capacity, and distort power dynamics within teams [13]. While advances in machine translation have been proposed to bridge language-based subgroups, these efforts typically focus on static, pre-meeting transcript exchanges of translations and ignore real-time dialect mediation.

D. *AI in Real-Time Communication*

Recent audits of ASR systems demonstrate persistent performance disparities across accents and dialects, with bias analyses finding that *"ASR errors directly correlate with regional dialectal features"* and that researchers often perpetuate misconceptions by treating accent as a speaker-only attribute [14]. Furthermore, existing affective-computing tools are trained on Western-centric corpora and deliver feedback only after meetings conclude, offering no on-the-fly clarification when miscommunication is the most costly.

E. *Blockchain Functionality in Multi-agents AI Systems (MAS)*

According to Karim et al. (2024), "Blockchain's immutable ledger and decentralized structure allow AI agents to operate independently while ensuring secure and verifiable interactions". It has been explored as a means to secure and verify decentralized agent interactions—enhancing immutability, auditability, and user agency in domains like Decentralized Finance (DeFi), autonomous robotics, and secure IoT., yet these studies seldom address linguistic fairness or integrate dialect-aware agents, leaving an opportunity to harness blockchain's trust guarantees within an MAS explicitly designed for real-time, inclusive communication.

F. *Gap Analysis & Need for IUUY*

No existing system concurrently integrates real-time, dialect-sensitive ASR/NLU, active-listening support for code-switchers, and decentralized verifiability via blockchain. The proposed *IUUY* MAS confronts this composite challenge, bridging crucial gaps to enable more inclusive and effective communication in globally distributed professional environments.

III. Methodology

A. *Research Objective*

To promote **active listening** and to mitigate **English-related communication breakdowns** in virtual environments resulting from dialectal variations, the approach involves the following:

- Auditing and diversely populating existing datasets for cultural biases in a non-WEIRD context,

- Designing an MAS capable of facilitating multi-cultural collaborations,
- Developing a prototype and consequently, the actual solution,
- Continuously evaluating and improving the system's effectiveness in reducing misunderstandings and its impact on team dynamics through controlled experiments.

B. *Development Methodology*

The Lean-Agile approach to system development emphasizes stakeholder collaboration and continuous improvement, which is particularly beneficial for complex, interdisciplinary and collaborative research projects [15]. Scrum, a key Agile framework known for its iterative delivery, rapid prototyping, and efficient user feedback cycles, is the preferred methodology for this research, as illustrated in Fig. 1. The research project will employ Continuous Integration and Continuous Delivery/Continuous Deployment (CI/CD) style of development. This aims to integrate code changes frequently, test them automatically, and deliver them to users or environments quickly and reliably. The three (3) phases: foundational research and data collection phase, the system development phase, and the evaluation phase, will run concurrently.

Phase 1: Foundational Research and Data Collection

This involves literature review, stakeholder interviews, review and update of diverse English corpora/datasets, and a deeper look into and collaboration with experts in Sociolinguistics and Psychology.

Phase 2: Development - Technical Design Framework (MAS + Blockchain)

Ab initio, this was a 7-agent design: **Agent 1** (Audio Preprocessing and Speaker Diarization), **Agent 2** (Dialect and Transfer Feature Detection), **Agent 3** (Cultural Nuance Interpreter), **Agent 4** (Lexical Clarification Generator), **Agent 5** (Contextual Intent Inference), **Agent 6** (UI Delivery), and **Agent 7** (Feedback and Bias Auditor).

However, according to Tian et al. (2025), relying on the assumption that the training data behind agents has a certain level of independence and the training objective is somewhat aligned, having more agents in a dialectal variation–trained MAS doesn't guarantee success, since fewer and cleaner handoffs (i.e., reduced coordination burdens) can lead to better outcomes. So, in line with the above logic, the 7 agents, especially during these initial stages of research, were found to rely on the same training data. It was on that note that the 7-agent system was consolidated to a 4-agent system. The 4-agent architecture was the result of grouping the original agents by their core function: **Input**, **Interpretation**, **User Experience**, and **Trust**.

1) ***Input Agent*** *- Ingestion and Diarization:* This consolidates Agent 1 (Audio Preprocessing and Speaker Diarization) of the initial proposed system.

- Core Function: Processes raw audio and prepares it for interpretation. This agent is the **"ears"** of the system.
- Output: A clean and time-stamped transcript with clear speaker labels.

2) ***Interpretation Agent*** *- Dialect Detection & Clarification:* This consolidates Agents 2 (Dialect Detection), 3 (Cultural Nuance), 4 (Lexical Clarification), and 5 (Contextual Intent) of the previous system architecture.

- Core Function: This **"brain"** of the system analyzes the transcribed text to understand its linguistic, cultural, and contextual meaning. This is where the main "magic" happens.
- Output: A data package containing the original phrase, the flagged "ambiguous" parts, and a set of suggested clarifications or translations.

3) ***UX Agent*** *- Delivery & Feedback:* This consolidates the previous Agent 6 (UI Delivery).

- Core Function: Presents the interpretations to the end-user in a seamless and nonintrusive way and makes provision for reinforcement learning from human feedback (RLHF), Bayesian update with IPFS logging. This is the **"active listening"** layer of the MAS.
- Output: The visual interface the user interacts with.

4) ***Trust Agent*** *- Decentralized Trust & Learning:* This consolidates Agent 7 (Feedback and Bias Auditor) and all blockchain concepts from the previous 7-agent system.

- Core Function: Manages blockchain integration, handles user feedback, and facilitates continuous, unbiased improvement of the entire system. This is the **"accountability"** layer.
- Output: Blockchain Integration, Decentralized IDs (DIDs) which would ensure user anonymity while verifying their feedback, Reinforcement Learning Loop where this agent collects all the user feedback, and Bias Auditing.

C. *Why are Fewer Agents More Powerful?*

By consolidating from 7 to 4 agents, the system retains its full functionality. Additionally, it is:

- **Leveraging Modern AI:** Letting a single, powerful transformer model handle the complex, interconnected task of interpretation, which is what they are designed for.
- **Reducing Complexity:** Having fewer "moving parts" and less potential for errors in communication between agents.
- **Creating a More Efficient Workflow:** The data flows logically from Input $\rightarrow$ Interpretation $\rightarrow$ Output $\rightarrow$ Trust/Feedback.

This streamlined 4-agent architecture provides a robust and scalable framework for building it.

D. *Interactional Architecture Summary*

As seen in Fig. 2, this architecture operates as a continuous, real-time loop, moving from audio input to user feedback and system improvement. The flow is designed for efficiency, with

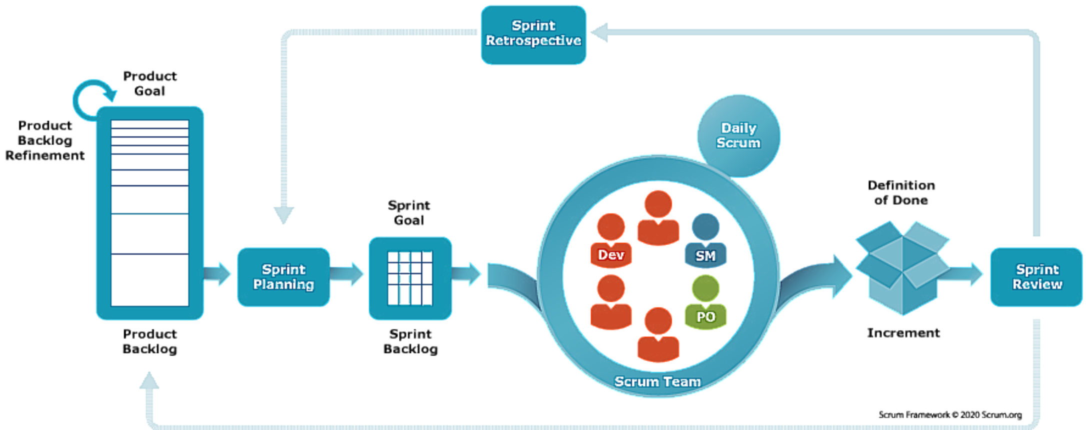

Fig. 1: Flow diagram of the scrum framework from scrum.org. The Scrum Team will be made up of the Scrum Master (SM), the Product Owner (PO), and the Development Team (Dev)—any developmental contributor to the *IUUY* system.

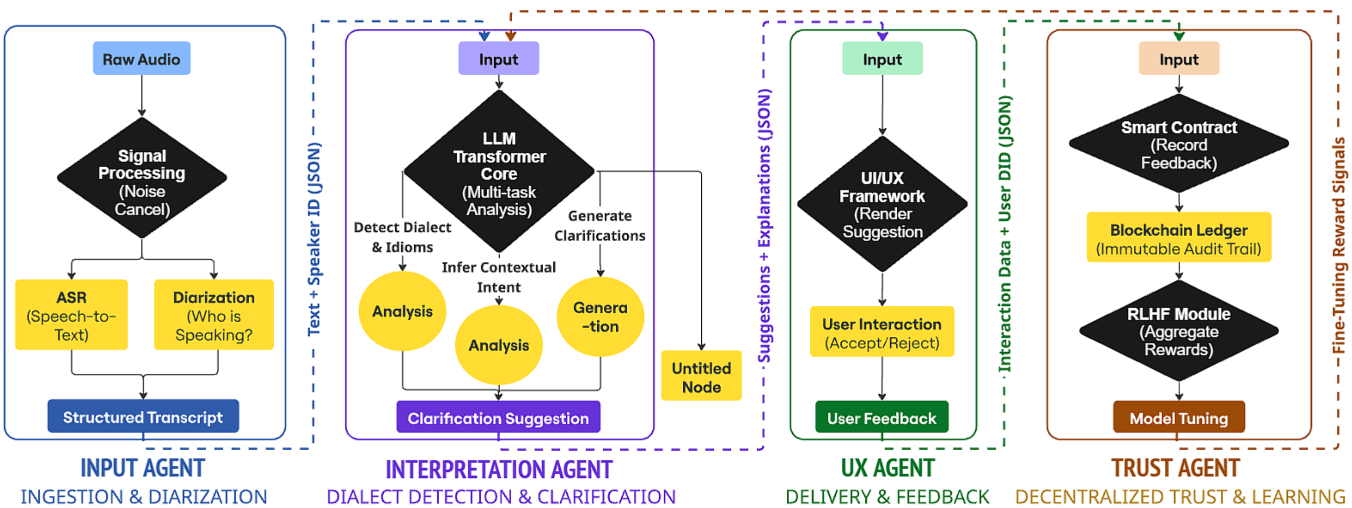

Fig. 2: A flowchart of the inner workings and interaction of the *IUUY* system .

each agent performing a specialized role before passing it on to the next.

Audio to Text (Agent 1 → Agent 2):

- The **Ingestion & Diarization Engine (Agent 1)** captures the live conversation audio. It cleans the signal, transcribes it to text, and crucially, assigns each part of the text to a specific speaker (diarization).
- This clean, speaker-labeled transcript is then passed in real-time to the core agent.

Text to Insight (Agent 2 → Agent 3):

- The **Core Interpretation Engine (Agent 2)** receives the transcript. It analyzes the text, dialogue history, and speaker identity to detect potential misinterpretations arising from dialect, cultural idioms, or ambiguous phrasing.
- It generates a set of clarifying suggestions or "universal English" translations designed to bridge the communication gap.
- This "insight package" (original text + suggestions) is then sent to the user-facing agent.

Insight to User (Agent 3 → Agent 4):

- The **User Experience (UX) & Delivery Agent (Agent 3)** presents these suggestions to the user through a non-intrusive interface (e.g., a subtle pop-up or sidebar note).
- The user interacts with these suggestions: accepting, rejecting, or ignoring them.
- This user interaction is the critical feedback event, which is immediately passed to the final agent.

Feedback to System (Agent 4 → Agent 2):

- The **Decentralized Trust & Learning Agent (Agent 4)** records the user's feedback on the blockchain, creating a secure and transparent audit trail.
- This feedback acts as a "reward signal" that is used to continuously retrain and fine-tune the **Core Interpretation Engine (Agent 2)**.

- This completes the loop, making the system smarter and more accurate with every user interaction, while the blockchain layer ensures the process is transparent and guards against bias.

E. *System Design and Development with Proof of Concept (PoC)*

Objective: Validate the core MAS pipeline, ingestion, emergent-LLM interpretation, and user feedback collection on blockchain, and demonstrate its ability to (a) correctly classify dialects, (b) rewrite utterances into standard English, and (c) log reinforcement signals immutably.

System Integration: This prototype was built upon the initial MAS prototype, moving from isolated component testing to an integrated system that processes authentic speech, identifies dialects, clarifies meanings, and incorporates real user feedback for ongoing improvement. This PoC aims to demonstrate that the MAS can operate end-to-end and deliver measurable value across various English dialect scenarios.

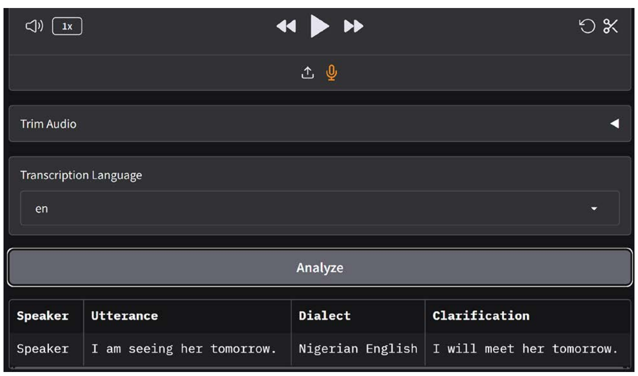

Fig. 3: *IUUY* prototype recognizing a particular utterance as Nigerian English and giving an alternative clarification.

System Architecture (as Implemented):

- Agent 1: Ingestion and Diarization Engine (WhisperX-based ASR with speaker labeling)
- Agent 2: Core Interpretation Engine (Hybrid dialect table + Gemini LLM, emergent dialect detection)
- Agent 3: UX/Delivery Agent (Gradio app for user-facing interface, transcript, and clarifications, although Streamlit was attempted)
- Agent 4: Decentralized Trust and RLHF Agent (Bayesian RLHF, feedback log, IPFS/Pinata blockchain storage, although NFT Change was attempted)

System Setup:

1) Environment
    - Colab notebook (GPU runtime) or local Python 3.11 environment
    - Key libraries: `openai-whisper`, `google-generativeai`, `gradio`, `pandas`, `requests`, `datasets`, `ffmpeg-python`, `yt-dlp` and more.
2) Agents Instantiation
   Agents 1 to 4 were instantiated.
3) Sample Data

Each clip of a small set of 10 audio clips representing various dialects was stored as ./samples/dialect/i.wav.

Gradio PoC Interface: Embedded in Colab, the UI has three panels:

Import / Record Audio Upload local `.wav` or paste a YouTube URL

Run Analysis

1) The “Analyze” button invokes the MAS pipeline.
2) Displays a 3-column table with Utterance, Dialect, and Clarification columns.

Submit Feedback

- For each row, the user marks “Correct” or “Needs Review”
- On click, calls the feedback loop.

AgentTrustLearning updates `belief_scores.csv` and pins feedback JSON to IPFS.

Download Beliefs Button to download the current Beta-distribution scores per dialect.

IV. Performance Evaluation

A. *Success Metrics*

The system successfully identifies dialects from both authentic and synthetic speech samples when pre-trained on specific datasets. User clarifications are rated as “helpful” or “correct” in over 80% of interactions. Feedback is securely stored and accessible via Pinata, while the RLHF loop facilitates measurable updates to the system’s belief scores.

B. *Test Scenarios*

The study involves uploading and analyzing audio samples from Nigerian, Indian, UK, American, and Korean English dialects. Users contribute corrections, enabling the MAS to learn and update its dialect table. Additionally, the performance of Gemini 2.5 Flash and Pro is compared on ambiguous samples through an emergent test in Tables I, II and III.

Table I shows a 90% overall accuracy for the proposed model across ten test clips per dialect, but this is skewed by its near-perfect identification of American and UK English. In contrast, the model shows reduced accuracy on Indian English and struggles with Nigerian and Korean English, highlighting a likely bias due to imbalanced training data that underrepresents non-Western dialects and their linguistic features. This disparity raises fairness concerns in real-world applications such as speech recognition and education, pointing to the need for more inclusive data and dialect-sensitive modeling to achieve equitable outcomes.

Table II shows the rating from the user experience survey with ten participants. The Gradio interface on key UX aspects achieved an average mean score of 4.5 and a standard deviation of 0.54. The consistently high mean scores across UX dimensions reflect a strong overall user experience, especially in output clarity and ease of use, with low standard deviations indicating broad user agreement. However, the slightly

TABLE I: Dialect Identification Accuracy

Dialect	Samples Tested	Correctly Identified	Accuracy (%)
Nigerian English	10	4	40%
Korean English	10	2	20%
Indian English	10	6	60%
American English	10	10	100%
UK English	10	9	90%
Overall	50	45	90%

TABLE II: User Experience Survey: UX aspects (1=poor, 5=excellent)

UX Aspect	**Measurement**	**Mean Score (1–5)**	**Std. Dev.**
Ease of Use	"How easy was it to upload and analyze audio?"	4.6	0.5
Responsiveness	"How quickly did results appear?"	4.4	0.6
Clarity of Output	"How clear and legible were the tables?"	4.7	0.4
Feedback Flow	"How intuitive was providing feedback?"	4.3	0.7
Overall Satisfaction	"How satisfied are you with the tool?"	4.5	0.5

lower score in feedback flow highlights a potential area for improvement in user interaction.

TABLE III: Clarity Evaluation: scale (1=poor, 5=excellent) for fidelity (how well meaning is preserved) and naturalness (how fluent the rewritten English sounds)

Utterance	**Clarified Output**	**Fidelity (avg)**	**Naturalness (avg)**	**Overall (avg)**
"I beg, let's go nau."	"Please, let's leave now."	4.7	4.3	4.5
"It's raining? I bring umbrella?"	"Is it raining? Should I bring an umbrella?"	4.5	4.2	4.35
"No issues, yaar."	"It's fine, friend."	4.8	4.6	4.7
"Do you wanna catch a movie later?"	"Do you want to see a movie later?"	4.9	4.8	4.85
"Could you pop round for tea?"	"Could you come over for tea?"	4.6	4.4	4.5

Table III presents five dialectal utterances evaluated for fidelity and naturalness, with scores ranging from 4.35 to 4.85. American and Indian English clips scored highest, while UK English and other strongly regional forms dipped slightly, hinting at nuance challenges. All reformulations scored above 4.0, achieving clear, fluent English without substantial loss of meaning.

V. Conclusion

This research not only improves active listening and fosters inclusion but also advances inclusive AI ethics in line with major international frameworks: the United States (US) AI Bill of Right (ensuring transparency and equity), the European Union (EU) AI Act's risk-based approach, and UNESCO's Recommendation on the Ethics of AI (endorsed by all United Nations (UN) member states). By dovetailing these initiatives with Nigeria's National AI Strategy and Korea's AI Guidelines, the project empowers diverse professionals to collaborate virtually. It reinforces global commitments to the UN Sustainable Development Goals.

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