# MTR-DuplexBench: Towards a Comprehensive Evaluation of Multi-Round Conversations for Full-Duplex Speech Language Models

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## Abstract

Full-Duplex Speech Language Models (FD-SLMs) enable real-time, overlapping conversational interactions, offering a more dynamic user experience compared to traditional half-duplex models. However, existing benchmarks primarily focus on evaluating single-round interactions, neglecting the complexities of multi-round communication. Evaluating FD-SLMs in multi-round settings poses significant challenges, including blurred turn boundaries in communication and context inconsistency during model inference. Also, existing benchmarks often focus solely on evaluating conversational features, neglecting other critical aspects. To address these gaps, we introduce MTR-DuplexBench, a novel benchmark designed for a comprehensive multi-round evaluation of FD-SLMs. MTR-DuplexBench not only segments continuous full-duplex dialogues into discrete turns for turn-by-turn assessment but also incorporates various evaluation aspects, including conversational features, dialogue quality, instruction following, and safety. Experimental results reveal that current FD-SLMs face difficulties in maintaining consistent performance across multiple rounds and evaluation dimensions, highlighting the necessity and effectiveness of our benchmark.[1]

## 1 Introduction

Speech Language Models (SLMs) are foundation models designed for seamless, end-to-end interaction with users through speech (Cui et al., 2024). These models excel in comprehending various aspects of user speech, including meaning, prosody, voice characteristics, and in generating appropriate responses. Most SLMs are built to support **half-duplex communication** (HD-SLMs), wherein the model first "listens" to a complete user query and then "speaks" the corresponding response. A more advanced subset of SLMs, known as Full-Duplex Speech Language Models (FD-SLMs), specializes in enabling **full-duplex communication**. This capability allows the model to concurrently listen and speak during real-time interactions, fostering complex conversational features, such as interruptions and backchannels, thereby creating a more dynamic and engaging user experience.

When evaluating FD-SLMs, existing benchmarks primarily assess the model's ability to interact in a single round of interaction. For instance, Full-Duplex-Bench (Lin et al., 2025c) generates scenarios where the user engages in continuous speech for one turn, pauses mid-turn, or interrupts the assistant. Full-Duplex-Bench v1.5 (Lin et al., 2025b) builds on this by introducing speech inputs with overlapping interruptions, backchannels, and similar dynamics. However, real-world conversations often unfold in a **multi-round** format, and evaluating FD-SLMs in such settings is crucial to ensure the model consistently delivers timely and high-quality speech even after multiple rounds of communication.

Multi-round communication evaluation for FD-SLMs is challenging, mainly due to the following features in the full duplex dialogues. **1) Blurred Turn Boundary.** Unlike HD-SLMs, where conversations are naturally organized in a turn-by-turn manner, full duplex communication occurs spontaneously, without adhering to a strict turn-taking structure. Consequently, there are no clear indicators marking the start or end of each speaking turn for either the user or the assistant. This lack of defined boundaries makes it difficult to assess the response quality for a specific communication round. **2) Context Inconsistency.** In natural full-duplex communication datasets, the user's speech in each round depends on the ground-truth assistant's responses from previous rounds. However, during evaluation, the model's responses to earlier

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[1]Code and data are available at: `https://github.com/ZhangHe0918/MTR-DuplexBench`



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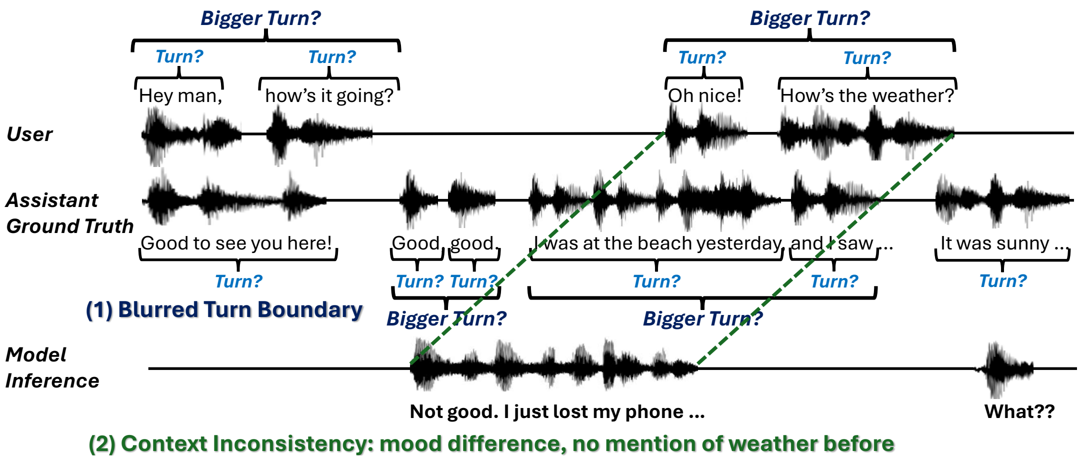


Figure 1: Illustration of the Blurred Turn Boundary and the Context Inconsistency challenges in the multi-round full duplex evaluations.

Table 1: Comparison of the supported features between MTR-DuplexBench and other full duplex benchmarks. MRD, TE, CF, DQ, IF represent Multi-round Dialogue, Turn-by-turn Evaluation, Conversational Features, Dialogue Quality, and Instruction Following, respectively.

| Benchmarks | MRD | TE | CF | DQ | IF | Safety |
|---|---|---|---|---|---|---|
| Full-Duplex-Bench | ✗ | ✗ | ✓ | ✓ | ✗ | ✗ |
| Full-Duplex-Bench v1.5 | ✗ | ✗ | ✓ | ✗ | ✗ | ✗ |
| Full-Duplex-Bench v2 | ✓ | ✗ | ✓ | ✗ | ✓ | ✓ |
| FD-Bench | ✓ | ✗ | ✓ | ✓ | ✗ | ✗ |
| Talking Turns | ✓ | ✗ | ✓ | ✗ | ✗ | ✗ |
| **MTR-DuplexBench** | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

rounds may diverge significantly from the ground truth, creating a context mismatch. This inconsistency leads the model to operate in scenarios that would never occur in real-world conversations, ultimately diminishing the reliability of the evaluation. Figure 1 illustrates the two challenges.

Another notable limitation of existing benchmarks is their predominant focus on evaluating FD-SLMs' ability to manage various conversational features, while largely overlooking other critical capabilities of the model, such as instruction following (Lou et al., 2024; Zhou et al., 2023; Zeng et al., 2023) and ensuring safe outputs (Shi et al., 2024; Sun et al., 2025; Li et al., 2024). These capabilities need to be evaluated accordingly since they pose unique challenges to FD-SLMs. For example, if the user keeps interrupting the model for multiple rounds, can the model still maintain expected behaviors (e.g., properly follow instructions)?

To address the challenges and limitations mentioned above, we introduce a novel benchmark, MTR-DuplexBench, designed to comprehensively evaluate FD-SLMs in a multi-round communication setting. First, our benchmark employs an innovative methodology to segment continuous full-duplex dialogues into discrete turns, enabling effective evaluation of FD-SLMs for each turn separately. This approach directly tackles key challenges of the blurred turn boundary and context inconsistency. Second, our benchmark provides a more comprehensive evaluation framework compared to existing benchmarks, encompassing aspects such as dialogue quality, conversational features, instruction following, and safety. This holistic approach ensures thorough and reliable assessments of FD-SLMs. Table 1 compares MTR-DuplexBench with other established benchmarks. To summarize our contributions:

1. We propose a novel benchmark, MTR-DuplexBench, for comprehensive evaluation of FD-SLMs in multi-turn interactions, covering conversational features, dialogue quality, instruction following, and safety.
2. We introduce a turn segmentation methodology for segmenting continuous full-duplex dialogues into discrete turns, enabling turn-by-turn evaluations of FD-SLMs.
3. We demonstrate through experiments that existing FD-SLMs struggle to maintain consistent performance across multiple rounds and evaluation dimensions, highlighting the necessity and effectiveness of our proposed benchmark.

## 2 Related Works

### 2.1 Speech Language Models

Speech Language Models (SLMs) refer to speech-based autoregressive foundation models that enable end-to-end spoken dialogue interactions (Cui et al., 2024). As mentioned before, SLMs can be categorized into HD-SLMs and FD-SLMs.

**Half Duplex Speech Language Models (HD-SLMs)** refer to the SLMs that enable "listening" and "speaking" in a turn-by-turn fashion. In this setup, the user provides a complete query to the model, which then generates the corresponding spoken response (Lakhotia et al., 2021; Kharitonov et al., 2021; Zhang et al., 2023). Therefore, HD-SLMs are designed to handle the concatenated sequence comprising the user query and the assistant's response. HD-SLMs are typically continually trained upon existing Text Large Language Model (TLM) (Zhao et al., 2023; Achiam et al., 2023) checkpoints through a two-stage process. **1) Pre-training.** In this initial stage, the model uses extensive speech data for autoregressive speech generation. This can involve unsupervised learning with pure speech data (Zhang et al., 2023; Wang et al., 2025a) or text-speech alignment pairs (Nguyen et al., 2025; Zeng et al., 2024) to transfer knowledge from text to speech. **2) Instruction Tuning.** After pre-training, the model is trained on speech instruction tuning datasets, enabling it to respond effectively to spoken queries (Xie and Wu, 2024; Fang et al., 2024). During inference, some HD-SLMs respond in speech directly (Hassid et al., 2023; Nguyen et al., 2025), while others first generate text responses as guidance and then produce the corresponding speech (Long et al., 2025; Chen et al., 2025; Xu et al., 2025).

**Full Duplex Speech Language Models (FD-SLMs)** refer to the SLMs that enable "listening" and "speaking" simultaneously to support advanced conversational features such as interruption and backchannel. FD-SLMs are typically built upon HD-SLMs, and they can be divided into two categories (Cui et al., 2025b). **1) Cascaded FD-SLMs** divide the full duplex dialogues into different states. The SLM then decides to listen or speak based on the current dialogue state (Ma et al., 2025; Xie and Wu, 2024; Wang et al., 2024). Cascaded FD-SLMs are typically trained on synthetic full duplex data to enable simple conversation features like interruption. **2) End-to-end FD-SLMs**, on the other hand, directly learns from the real-world full duplex data to enable more natural, human-like conversational dynamics (Wang et al., 2025a; Défossez et al., 2024; Cui et al., 2025b).

### 2.2 Full Duplex Benchmarks

Full duplex benchmarks focus on evaluating FD-SLMs on various features related to full duplex communications. Most full duplex benchmarks focus on evaluating one round of spoken interactions. Specifically, Full-Duplex-Bench (Lin et al., 2025c) devise one round of spoken prompts to evaluate FD-SLM's ability for pause handling, backchanneling, smooth turn taking, and user interruptions. Full-duplex-bench v1.5 (Lin et al., 2025b) extends the evaluation scenarios to overlapping speech, but is still limited to one round of interaction.

Other full-duplex benchmarks incorporate multi-round spoken prompts but prioritize overall model response quality over individual round performance. They also focus on single scenarios, limiting comprehensive assessments of FD-SLM's multi-round interaction capabilities. For example, FD-Bench (Peng et al., 2025) uses up to five rounds of user prompts, mainly addressing user interruptions with synthetic speech. In contrast, our benchmark provides diverse evaluations for multi-round full-duplex communication using both natural and synthetic dialogue data. Similarly, Talking Turns (Arora et al., 2025) includes multi-round data but solely predicts turn-taking timings without round-by-round dialogue evaluation. Moreover, their data collection relies on human interactions with various models, making it resource-intensive to scale and adapt to new models. Our benchmark, however, implements an automated evaluation pipeline with round-by-round metrics, removing the need for human intervention. Additionally, concurrent work by Lin et al. (2025a) evaluates multi-round full-duplex interactions across four scenarios (Daily, Correction, Entity Tracking, and Safety), focusing on task-level outcomes instead of turn-level behaviors. It utilizes a separate Speech LLM as an automated examiner, which does not guarantee consistent interaction data for the same task, limiting evaluation stability. In contrast, our benchmark uses the same evaluation data for each round, allowing for stable assessments and fair model comparisons.

## 3 MTR-DuplexBench

This section illustrates the technical details of our proposed MTR-DuplexBench benchmark. We start by introducing the full duplex turn segmentation methodology, which segments continuous full duplex dialogues into discrete turns to enable turn-by-turn evaluation. Subsequently, we outline the overall structure of the benchmark, encompassing all evaluation dimensions.

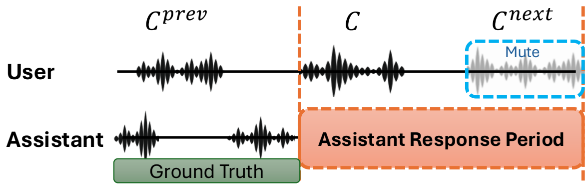


Figure 2: Illustration of the assistant response period in the full duplex turn segmentation methodology.

### 3.1 Full Duplex Turn Segmentation Methodology

The full-duplex turn segmentation methodology is designed to address the challenges of blurred turn boundaries and context inconsistency in real-world full duplex dialogues and enable turn-by-turn evaluations. It contains an algorithm to identify the start and end points of each user turn boundary within a full-duplex dialogue. Then, the appropriate time period for the assistant's response is determined accordingly. We provide an overview of the algorithm below, with the complete version detailed in Algorithm 1.

The turn segmentation algorithm is to address the *blurred turn boundary* challenge and can be divided into four steps. **1) Information Extraction.** Initially, given speech audio from both channels $A_c$ where $c \in$ user, assistant, we employ the Whisper-timestamped package (Louradour, 2023) in conjunction with Silero Voice Activity Detection (VAD) (Team, 2024) and the medium-sized Whisper model (Radford et al., 2023). These tools extract the transcriptions and the start/end timestamps of each VAD segment, denoted as $S^c \leftarrow \text{Extract}(A_c) = \{(T_j^{start}, T_j^{end}, text_j^c)\}_{j=1}^n$. The VAD segments are fragmented and typically correspond to portions of a user turn. **2) GPT Turn Segmentation.** Accurately identifying user turn boundaries involves understanding both the content and timestamp information. For this purpose, we utilize GPT-4o to automate the segmentation task. Before processing, the segments are sorted by start time. GPT-4o then determines the turn boundaries, denoted as $Turns \leftarrow \text{GPT-4o}(\text{sort}(S^{\text{user}} \cup S^{\text{assistant}}))$. The full GPT prompt for this task is presented in Figure 3. **3) Majority Voting with Clustering and Filtering.** Despite its efficiency, the GPT segmentation results exhibit variability across different trials. To address this, a majority voting mechanism is implemented to ensure stability. Specifically, the GPT segmentation process is repeated six times, and the results are aggregated into candidate turns. Candidate turns are formed iteratively by grouping extracted turns, where a new $Turn$ merges into an existing candidate turn $C$ if there is at least a 30% time overlap, i.e., $C.turns \leftarrow C.turns \cup Turn$ and $C.votes \leftarrow C.votes + 1$, and the start/end timestamps of the candidate turn are updated to the median start/end times of all merged turns, i.e., $C.start/end \leftarrow \text{median}(t^{\text{start/end}} : t \in C.turns)$. **4) Final Overlap Resolution.** In rare cases, grouped candidate turns may still exhibit time overlaps. To resolve this, all overlapping candidate turns are merged to form the final user turns, denoted as $FinalTurns \leftarrow (C.start, C.end) : C \in Candidates$.

After segmenting the user's turns, we allocate a specific time period for the assistant to respond to each turn, addressing the challenge of *context inconsistency*. In particular, the assistant is tasked solely with formulating responses for the current turn, while the responses for all previous turns in the assistant channel are populated with the ground truth speech. This ensures that there is no context mismatch between the user and assistant channels. The assistant's response period spans from the start time of the current user turn to the end time of the next user turn, i.e., $[C.start, C^{\text{next}}.end]$, during which the next user turn is muted, as illustrated in Figure 2. This design ensures that the assistant responds fully, even if it continues after the user begins speaking in the subsequent turn.

### 3.2 Evaluation Dimensions

In MTR-DuplexBench, we incorporate four evaluation dimensions to support comprehensive evaluation of various capabilities of FD-SLMs, which include conversational features, dialogue quality, instruction following, and safety. For each dimension, we introduce the overall setting, the Research Questions (RQs), the data curated, and the evaluation pipeline and metrics used. Table 2 summarizes the evaluation dimensions included, along with relevant statistics and attributes.

#### 3.2.1 Conversational Features

Conversational features refer to distinct real-time communication patterns found in full-duplex interactions, often characterized by the timing and flow of the dialogue. Following Lin et al. (2025c) and Lin et al. (2025b), we identify five key features: smooth turn-taking, interruption, pause handling, background speech, and backchanneling. Concisely, in terms of an FD-SLM, smooth turn-taking describes the ability to seamlessly take its turn to

| Dimension | Source | # Data | # Rounds (AVG) | Data Type | Metrics |
|---|---|---|---|---|---|
| Conversational Features | Self-generated | 200 | 10 | Synthetic | Success Rate |
| Dialogue Quality | Candor | 200 | 5.88 | Natural | GPT-score |
| Instruction Following | Llama Question | 300 | 10 | Synthetic | Success Rate |
| Safety | AdvBench | 520 | 10 | Synthetic | Refusal Rate |

Table 2: Statistics of different evaluation dimensions within MTR-DuplexBench.

respond once the user's query has concluded. Interruption refers to the capacity to stop speaking when the user interjects. Pause handling involves staying silent during brief pauses in the user's speech. Background speech handling is the ability to disregard irrelevant background sounds not originating from the user. Finally, backchanneling denotes the ability to provide acknowledgment cues during the user's speech. **Our core novelty** lies in adapting the conversational features to the multi-round communication setting, as outlined in the RQs below.

**Research Question(s). RQ1.1:** Can FD-SLMs maintain their performance when handling multiple rounds of a single conversational feature? **RQ1.2:** Can FD-SLMs maintain their performance when handling multiple rounds of multiple conversational features combined together, compared to a single feature?

**Data Curated.** Since we need to manually create multi-round evaluation data with specified conversational features, we utilize synthetic data in this evaluation dimension. Specifically, we leverage GPT-4o (Hurst et al., 2024) to first generate 200 10-round text conversation data, and then utilize CosyVoice 2 (Du et al., 2024) to synthesize them into speech. The complete prompt for GPT-4o to generate the text data is presented in Figure 5.

**Evaluation Pipeline and Metric.** We support up to ten rounds of conversation for the conversational feature evaluation, using the synthesized speech data. In each round, any feature excluding backchanneling can be selected[2], with the evaluation pipeline being adjusted and the model response evaluated accordingly. The main metric for each feature is *success*, which is to measure if the model has successfully handled the feature in the current round. Formally, success is defined as

$$success = \begin{cases} 1, & \text{if the feature is successfully handled} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Therefore, a higher *success rate* is desirable. Note that the criteria defining *success* for each feature vary slightly and are primarily enhanced from metrics used in prior studies, so we put their detailed formal definitions in Appendix A. Additionally, we measure the *latency (seconds)* of the model response and the *backchannel frequency* that occurred in each interaction round.

### 3.2.2 Dialogue Quality

Dialogue quality refers to the overall meaningfulness and coherence of the dialogue generated by FD-SLMs. It is a central focus in the evaluation of FD-SLMs, as their primary purpose is to facilitate natural spoken conversational experiences. This approach differs from HD-SLMs, where the evaluation emphasizes the model's intelligence, often assessed through challenging Question-Answering (QA) tasks. In contrast, FD-SLMs prioritize creating seamless and engaging conversational interactions over demonstrating high levels of intelligence.

**Research Question(s). RQ2:** Can FD-SLMs produce meaningful and coherent dialogues when engaging in natural conversations?

**Data Curated.** To more accurately simulate real-world interaction scenarios, we choose to use natural spoken dialogues—a subset of the Candor dataset—as the evaluation data. The Candor dataset is chosen because it is a widely recognized, full-duplex dialogue dataset consisting of collected real human speech. Additionally, it has not been used as part of the training data for popular FD-SLMs, making it ideal for ensuring a fair evaluation. The final dataset consists of 200 dialogues, and each dialogue lasts 120 seconds.

**Evaluation Pipeline and Metric.** We conduct a turn-by-turn evaluation to assess dialogue quality. Each 120-second dialogue is divided into distinct interaction rounds using the full-duplex turn segmentation methodology described in Section 3.1. Subsequently, model inference is performed on each extracted interaction round, generating a double-channel audio output. Following Cui et al. (2025b), we employ the *GPT-score* as the final evaluation metric. To implement this, we first transcribe the double-channel audio

[2] Backchanneling can occur at any point in the dialogue, making it independent of any specific interaction round.

with sentence-level timestamp information using Whisper-large-v3 (Radford et al., 2023) alongside the stable-ts package (Jian, 2023). The transcriptions from the two channels are then aligned based on the start times of each sentence, creating a time-synchronized dialogue. Next, GPT-4o (Hurst et al., 2024) is utilized to evaluate the overall dialogue quality on a scale of 0-5. The complete GPT-4o prompt used for this assessment is detailed in Figure 4. Finally, the *GPT-scores* for all rounds are averaged to derive the final score.

#### 3.2.3 Instruction Following & Safety

Instruction following refers to the ability of FD-SLMs to properly address user queries, while safety pertains to their capacity to prevent the generation of harmful or toxic outputs when prompted. We integrate these two critical aspects into MTR-DuplexBench because it is essential to develop an FD-SLM that is not only practical and effective but also safe, alongside its duplex communication features. Here, we combine the discussion of these two tasks, given that they share similar research questions, evaluation methods, and other aspects. Similar to conversational features, our core novelty lies in adapting these two tasks for multi-round communication within the context of full duplex spoken interactions.

**Research Question(s). RQ3.1:** Can FD-SLMs demonstrate good instruction following and safety abilities in multiple rounds of normal interactions? **RQ3.2:** Can FD-SLMs maintain the instruction following and safety performance when being interrupted in every round of interaction?

**Data Curated.** For instruction following, we utilize the existing Llama Question dataset in the OpenAudioBench (Li et al., 2025), which includes 300 spoken queries. For safety, we utilize the existing AdvBench dataset (Zou et al., 2023) included in the Voicebench (Chen et al., 2024), which includes 520 spoken queries.

**Evaluation Pipeline and Metric.** We support up to ten rounds of conversation. In each round, a random spoken query is selected as the user speech, and the interaction fashion can be selected from either a smooth turn-taking or an interruption round. We leverage the *success/refusal rate*, powered by a binary decision by GPT-4o, to determine whether the model successfully follows the user instruction or avoids generating harmful content. The complete GPT-4o prompt is in Figure 6 and Figure 7.

## 4 Experiments

This section begins by introducing the baseline models considered in the evaluation. Subsequently, we outline the experimental settings and present the evaluation results for each evaluation dimension.

### 4.1 FD-SLM Baselines

Following Lin et al. (2025c), we mainly evaluate the only two available open-source FD-SLMs—Moshi (Défossez et al., 2024) and Freeze-Omni (Wang et al., 2024)—which represent end-to-end and cascaded FD-SLMs (Section 2.1). We also include one HD-SLM and one cascaded approach[3] for comparing behavior between full duplex and non-full duplex models. Specifically, we use VocalNet (Wang et al., 2025b) to serve as the HD-SLM, and we use the Bailing package (wwbin2017, 2024) with SenseVoice (An et al., 2024), GPT-4o (Hurst et al., 2024), and ChatTTS (2noise, 2024), to serve as the cascaded approach.

**Remark 1.** *Since HD-SLMs and cascaded approaches do not natively support simultaneous listening and speaking, we implement the approaches with the assumption that the model would stop speaking immediately when user speech is detected.*

### 4.2 Experimental Results

#### 4.2.1 Conversational Features

To address **RQ1.1**, we evaluate whether the models can maintain their performance for handling a single conversational feature across multiple interaction rounds. We carry out ten-round evaluations focusing on a single feature and compute the success rate for each model. For instance, the column "Pause Handling" represents scenarios where each of the ten rounds requires the model to effectively manage the pause handling feature. The results are presented in Table 3, where we report the averaged metrics[4] across a number of rounds, highlighting the following key findings. **1) Consistent performance degradation with an increasing number of interaction rounds.** Across all four conversational features, the success rate of the SLMs consistently decreases as the number of interaction rounds increases. **2) Consistent latency grows as interaction rounds increase.** This observation is also consistent across the four conversational

[3] Automatic Speech Recognition (ASR) + Large Language Model (LLM) + Text-to-speech Synthesis (TTS).

[4] For example, 1-5 represents the averaged metrics from round 1 to round 5.

| SLM | Smooth Turn-taking | | | | Interruption | | | | Pause Handling | | | | Background Speech | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Success Rate (%) ↑** | | | | | | | | | | | | | | | |
| | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** |
| Moshi | 73.00 | 66.25 | 62.80 | 57.40 | 72.50 | 63.25 | 57.90 | 54.20 | 93.50 | 88.50 | 86.70 | 84.80 | 53.00 | 42.75 | 35.30 | 25.70 |
| Freeze-Omni | 69.00 | 61.50 | 47.10 | 36.35 | 76.00 | 73.58 | 66.02 | 56.64 | 89.00 | 87.75 | 79.30 | 68.45 | 0.54 | 1.30 | 0.92 | 1.06 |
| VocalNet | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cascaded | 98.50 | 98.25 | 98.90 | 98.95 | 99.50 | 98.49 | 97.69 | 96.33 | 100.0 | 100.0 | 100.0 | 100.0 | 0.00 | 0.00 | 0.00 | 0.00 |
| | **Latency (s) ↓** | | | | | | | | | | | | | | | |
| | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** |
| Moshi | 0.64 | 0.76 | 0.86 | 0.85 | 0.54 | 0.50 | 0.53 | 0.64 | 0.58 | 0.64 | 0.78 | 0.92 | 0.65 | 1.28 | 1.64 | 2.03 |
| Freeze-Omni | 0.61 | 0.52 | 0.42 | 0.32 | 1.62 | 1.74 | 1.86 | 1.52 | 0.70 | 0.68 | 0.56 | 0.40 | 1.03 | 0.87 | 0.69 | 0.53 |
| VocalNet | 1.18 | 1.16 | 1.17 | 1.20 | 1.46 | 1.78 | 2.00 | 1.79 | 1.43 | 1.76 | 1.61 | 1.60 | 1.50 | 1.83 | 1.86 | 1.88 |
| Cascaded | 9.57 | 10.00 | 10.00 | 10.72 | 9.30 | 10.53 | 12.20 | 12.30 | 9.59 | 9.64 | 9.33 | 9.98 | 8.57 | 9.68 | 9.62 | 9.19 |
| | **Backchannel Frequency ↑** | | | | | | | | | | | | | | | |
| | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** |
| Moshi | 0.27 | 0.15 | 0.08 | 0.23 | 0.14 | 0.08 | 0.05 | 0.14 | 0.15 | 0.08 | 0.05 | 0.13 | 0.04 | 0.04 | 0.23 | 0.66 |
| Freeze-Omni | 0.02 | 0.03 | 0.04 | 0.04 | 0.09 | 0.06 | 0.05 | 0.04 | 0.06 | 0.06 | 0.06 | 0.05 | 0.02 | 0.02 | 0.04 | 0.04 |
| VocalNet | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cascaded | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table 3: SLM performance in the multi-round evaluation for handling a single conversational feature.

| SLM | S | | | | S + I | | | | S + I + P | | | | S + I + P + B | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Success Rate (%) ↑** | | | | | | | | | | | | | | | |
| | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** |
| Moshi | 73.00 | 66.25 | 62.80 | 57.40 | 69.50 | 63.00 | 58.70 | 54.45 | 69.00 | 62.75 | 59.00 | 54.30 | 53.50 | 48.25 | 43.40 | 37.55 |
| Freeze-Omni | 69.00 | 61.50 | 47.10 | 36.35 | 67.01 | 65.50 | 53.71 | 43.40 | 59.13 | 58.50 | 50.05 | 39.06 | 34.36 | 30.59 | 24.70 | 19.51 |
| VocalNet | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 100.0 | 50.25 | 50.75 | 48.94 | 50.50 |
| Cascaded | 98.50 | 98.25 | 98.90 | 98.95 | 99.00 | 98.25 | 98.50 | 98.25 | 98.50 | 97.50 | 97.80 | 97.65 | 50.00 | 49.75 | 47.80 | 49.20 |
| | **Latency (s) ↓** | | | | | | | | | | | | | | | |
| | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** |
| Moshi | 0.64 | 0.76 | 0.86 | 0.85 | 0.48 | 0.40 | 0.61 | 0.66 | 0.51 | 0.47 | 0.57 | 0.71 | 0.68 | 0.74 | 0.95 | 1.31 |
| Freeze-Omni | 0.61 | 0.52 | 0.42 | 0.32 | 0.63 | 0.90 | 0.79 | 0.59 | 0.35 | 0.74 | 0.69 | 0.53 | 0.53 | 0.86 | 0.72 | 0.55 |
| VocalNet | 1.18 | 1.16 | 1.17 | 1.20 | 1.12 | 1.51 | 1.55 | 1.52 | 1.10 | 1.48 | 1.55 | 1.49 | 1.16 | 1.61 | 1.63 | 1.61 |
| Cascaded | 9.57 | 10.00 | 10.00 | 10.72 | 8.96 | 9.66 | 9.48 | 9.43 | 8.57 | 9.43 | 9.55 | 9.34 | 9.93 | 11.19 | 11.84 | 11.17 |
| | **Backchannel Frequency ↑** | | | | | | | | | | | | | | | |
| | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** | **1** | **1-2** | **1-5** | **1-10** |
| Moshi | 0.27 | 0.15 | 0.08 | 0.23 | 0.02 | 0.02 | 0.03 | 0.11 | 0.02 | 0.02 | 0.03 | 0.20 | 0.01 | 0.02 | 0.02 | 0.30 |
| Freeze-Omni | 0.02 | 0.03 | 0.04 | 0.04 | 0.01 | 0.02 | 0.04 | 0.04 | 0.02 | 0.02 | 0.04 | 0.04 | 0.02 | 0.03 | 0.04 | 0.04 |
| VocalNet | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Cascaded | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Table 4: SLM performance in the multi-round evaluation for handling multiple conversational features combined.

| Model | GPT-score | Rescaled GPT-score | # Words |
|---|---|---|---|
| Moshi | 1.86 | 3.13 | 21 |
| Freeze-Omni | 2.07 | 3.48 | 36 |
| VocalNet | 2.35 | 3.96 | 24 |
| Cascaded | 1.30 | 2.19 | 10 |

Table 5: Dialogue quality evaluation result. # Words denote the average number of words per response.

features, highlighting a critical challenge for most SLMs, where the communication experience becomes less natural due to higher latency. This finding also underscores that the commonly reported *first-package latency* (Long et al., 2025; Shih et al., 2025) is insufficient for a fair evaluation of latency. Therefore, we advocate that future research should report multi-round latency for a more comprehensive assessment. **3) HD-SLM and cascaded approaches handle most features perfectly except Background Speech.** Their half-duplex design ensures a response after fully processing the user's utterance. However, they become completely ineffective under Background Speech, since any detected user input automatically makes them stop speaking. **4) The cascaded approach exhibits extremely high latency.** Cascading three complex modules significantly increases interaction latency. Although streaming the entire pipeline could mitigate this latency, it would require custom model training and optimization, thus limiting the use of off-the-shelf system components.

While the single-feature evaluation effectively demonstrates a model's capability to manage specific features, real-world speech interactions typically involve multiple features within a single conversation. Hence, we further assess whether the models can sustain their performance when handling combined conversational features, as compared to the single-feature evaluation (**RQ1.2**). The results are shown in Table 4. Specifically, we first use ten rounds of smooth turn-taking as the baseline (S). Next, we combine smooth turn-taking with interruption (S+I), adding pause handling (S+I+P), and include background speech (S+I+P+B), respectively. We note that for each feature addition, a round is randomly selected to introduce the new feature within every two rounds.[5] While most results align with the findings from **RQ1.1**, we note an additional observation: **the SLMs' performance consistently degrades with an increasing number of features.** This demonstrates that managing complex combined conversational features, which frequently occur in real-world scenarios, presents a significant challenge for SLMs.

### 4.2.2 Dialogue Quality

To address **RQ2**, we assess the overall dialogue quality of FD-SLMs using the turn-segmented dataset outlined in Section 3.2.2. Similar to the findings in Cui et al. (2025b), we observe that GPT-4o tends to assign conservative scores—the ground truth dialogues achieve an average GPT-score of 2.97. Therefore, we rescale the original GPT-scores from 0-2.97 to 0-5. We highlight the following observations based on the results in Table 5. **1) Enhanced full duplex capabilities are associated with a decrease in the meaningfulness of dialogue semantics.** End-to-end FD-SLM (Moshi, 3.13) performs poorer than cascaded FD-SLM (Freeze-Omni, 3.48), and the HD-SLM (VocalNet, 3.96) performs the best. **2) The cascaded approach achieves the lowest GPT score.** This counterintuitive finding is primarily attributable to the significantly high latency of the cascaded method (see Table 3), which prevents the model from completing its responses within the specified time period. The substantial decrease in the number of words per response from the cascaded approach (10 vs. 20+) further supports this conclusion, highlighting that latency is a critical factor influencing the full duplex interaction experience.

### 4.2.3 Instruction Following & Safety

We assess the model's instruction following and safety abilities in a multi-round, full-duplex communication setting. The Llama Question/AdvBench dataset is reorganized into 100 evaluation samples, each consisting of 10 rounds. For each round, the data is randomly selected from the original pool of audio samples. To answer **RQ3.1**, we evaluate the instruction following and safety capabilities of baseline models, where all the interactions are conducted through smooth turn-taking rounds. The results, as shown in Table 6 and Table 7 (w/ Smooth Turn-taking), yield the following observations. **1) Moshi performs worse than all other baselines on both tasks.** Even in the initial round, Moshi shows the lowest *success/refusal rate*. **2) Moshi is the only SLM whose instruction-following ability significantly deteriorates as the number of interaction rounds increases.** The above two observations underscore the challenges in maintaining consistent instruction-following performance when developing truly e2e FD-SLMs. **3) All baselines demonstrate a strong safety ability and maintain consistent safety performance across various interaction rounds.** Notably, the refusal rates reported in Table 7 are consistently at or above 90%. This indicates that ensuring safety alignment is a more manageable task than achieving effective instruction following.

| SLM | w/ Smooth Turn-taking | | | | w/ Interruption | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 1-2 | 1-5 | 1-10 | 1 | 1-2 | 1-5 | 1-10 |
| Moshi | 68.0 | 61.3 | 53.7 | 41.9 | 69.0 | 60.5 | 51.8 | 42.3 |
| Freeze-Omni | 85.0 | 85.5 | 88.2 | 86.5 | 84.2 | 85.6 | 86.5 | 85.5 |
| VocalNet | 92.0 | 94.0 | 92.8 | 92.6 | 92.0 | 94.0 | 93.0 | 93.3 |
| Cascaded | 77.0 | 76.5 | 80.2 | 81.1 | 79.0 | 80.9 | 80.1 | 78.9 |

Table 6: Success rate of the multi-round instruction-following evaluation on various SLMs.

| SLM | w/ Smooth Turn-taking | | | | w/ Interruption | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 | 1-2 | 1-5 | 1-10 | 1 | 1-2 | 1-5 | 1-10 |
| Moshi | 90.0 | 89.5 | 89.8 | 91.0 | 93.0 | 91.5 | 89.0 | 90.7 |
| Freeze-Omni | 100.0 | 100.0 | 99.8 | 99.7 | 99.0 | 99.3 | 99.2 | 99.5 |
| VocalNet | 94.8 | 95.9 | 98.4 | 99.1 | 94.8 | 96.9 | 98.8 | 99.4 |
| Cascaded | 96.4 | 96.3 | 95.8 | 97.2 | 94.3 | 96.6 | 97.0 | 97.8 |

Table 7: Refusal rate of the multi-round safety evaluation on various SLMs.

One of the key features of full-duplex communication is its ability to handle user interruptions effectively. To ensure seamless functionality, models must be robust enough to manage multiple rounds of interruptions while maintaining expected behavior. To evaluate this capability, we conduct the same instruction following and safety assessments by modifying all interactions from smooth turn-taking to interruptions (**RQ3.2**). As illustrated in Table 6 and Table 7 (w/ Interruption), all baselines exhibit no significant difference in performance between scenarios with smooth turn-taking and those with interruptions, demonstrating their robustness in maintaining performance under user disruptions.

[5]That means the new-feature rounds are randomly selected from rounds [1-2], [3-4], ..., [9-10].

## 5 Conclusion

In this work, we present MTR-DuplexBench, a novel benchmark for comprehensively evaluating Full Duplex Speech Language Models (FD-SLMs) in multi-round conversational scenarios. Our proposed full-duplex turn segmentation methodology effectively addresses the challenges of blurred turn boundaries and context inconsistency for the dialogue quality evaluation. Beyond this, MTR-DuplexBench is the first benchmark to incorporate a wide range of evaluation dimensions—including dialogue quality, conversational features, instruction following, and safety—enabling thorough and reliable assessments of FD-SLMs. Experimental results demonstrate that existing FD-SLMs struggle to maintain performance across these dimensions in multi-round interactions, highlighting the need for developing more robust models.

## Limitations

While MTR-DuplexBench provides a comprehensive framework for evaluating FD-SLMs in multi-round conversational scenarios, limitations remain. Specifically, the benchmark relies on a combination of natural and synthetic datasets, which may not fully capture the diversity and unpredictability of real-world conversations. Additionally, the benchmark focuses primarily on English speech interactions, limiting its applicability to multilingual or cross-lingual FD-SLMs. Future efforts could address the limitations by enhancing the diversity of full-duplex conversational data and broadening the evaluation to include a wider range of languages. Furthermore, our conversational feature design strictly follows those defined in prior full-duplex benchmarks (e.g., Full-Duplex-Bench) to ensure comparability and ease of extension to multi-round settings. As a result, certain aspects, such as user backchannels, are not explicitly evaluated. Future work could expand the feature set to cover a broader range of interaction dynamics.

Another limitation of our methodology is the variance in evaluation design across different dimensions, which is necessitated by the inherent differences between natural and synthetic data. For dialogue quality assessment—which relies on natural human conversations—we employ turn segmentation and teacher-forced inference. This is essential to prevent the blurred turn boundary and context-mismatch problems, as the static user audio heavily depends on the historical context that an unguided model might diverge from. However, we acknowledge that teacher-forcing introduces a gap between the evaluation setup and a model's true, unguided inference trajectory. Conversely, our evaluations for conversational features, instruction following, and safety do not use teacher forcing. Instead, they rely on synthetic or disjoint multi-turn data, allowing the model to autoregressively build upon its own past outputs. This is feasible because conversational features primarily evaluate timing mechanics, and the instruction-following/safety queries are independent across turns, naturally avoiding context mismatch. Future iterations of this benchmark could explore unified evaluation paradigms that bridge the gap between complex natural data and true end-to-end multi-round inference.

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## References

2noise. 2024. Chattts: A generative speech model for daily dialogue. https://github.com/2noise/ChatTTS. GitHub repository.

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, and 1 others. 2023. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*.

Keyu An, Qian Chen, Chong Deng, Zhihao Du, Changfeng Gao, Zhifu Gao, Yue Gu, Ting He, Hangrui Hu, Kai Hu, and 1 others. 2024. Funaudiollm: Voice understanding and generation foundation models for natural interaction between humans and llms. *arXiv preprint arXiv:2407.04051*.

Siddhant Arora, Zhiyun Lu, Chung-Cheng Chiu, Ruoming Pang, and Shinji Watanabe. 2025. Talking turns: Benchmarking audio foundation models on turn-taking dynamics. *arXiv preprint arXiv:2503.01174*.

Qian Chen, Yafeng Chen, Yanni Chen, Mengzhe Chen, Yingda Chen, Chong Deng, Zhihao Du, Ruize Gao, Changfeng Gao, Zhifu Gao, and 1 others. 2025. Minmo: A multimodal large language model for seamless voice interaction. *arXiv preprint arXiv:2501.06282*.

Yiming Chen, Xianghu Yue, Chen Zhang, Xiaoxue Gao, Robby T Tan, and Haizhou Li. 2024. Voicebench: Benchmarking llm-based voice assistants. *arXiv preprint arXiv:2410.17196*.

Wenqian Cui, Xiaoqi Jiao, Ziqiao Meng, and Irwin King. 2025a. Voxeval: Benchmarking the knowledge understanding capabilities of end-to-end spoken language models. *arXiv preprint arXiv:2501.04962*.

Wenqian Cui, Dianzhi Yu, Xiaoqi Jiao, Ziqiao Meng, Guangyan Zhang, Qichao Wang, Yiwen Guo, and Irwin King. 2024. Recent advances in speech language models: A survey. *arXiv preprint arXiv:2410.03751*.

Wenqian Cui, Lei Zhu, Xiaohui Li, Zhihan Guo, Haoli Bai, Lu Hou, and Irwin King. 2025b. Think before you talk: Enhancing meaningful dialogue generation in full-duplex speech language models with planning-inspired text guidance. *arXiv preprint arXiv:2508.07375*.

Alexandre Défossez, Laurent Mazaré, Manu Orsini, Amélie Royer, Patrick Pérez, Hervé Jégou, Edouard Grave, and Neil Zeghidour. 2024. Moshi: a speech-text foundation model for real-time dialogue. *arXiv preprint arXiv:2410.00037*.

Zhihao Du, Changfeng Gao, Yuxuan Wang, Fan Yu, Tianyu Zhao, Hao Wang, Xiang Lv, Hui Wang, Chongjia Ni, Xian Shi, and 1 others. 2025. Cosyvoice 3: Towards in-the-wild speech generation via scaling-up and post-training. *arXiv preprint arXiv:2505.17589*.

Zhihao Du, Yuxuan Wang, Qian Chen, Xian Shi, Xiang Lv, Tianyu Zhao, Zhifu Gao, Yexin Yang, Changfeng Gao, Hui Wang, and 1 others. 2024. Cosyvoice 2: Scalable streaming speech synthesis with large language models. *arXiv preprint arXiv:2412.10117*.

Qingkai Fang, Shoutao Guo, Yan Zhou, Zhengrui Ma, Shaolei Zhang, and Yang Feng. 2024. Llama-omni: Seamless speech interaction with large language models. *arXiv preprint arXiv:2409.06666*.

Michael Hassid, Tal Remez, Tu Anh Nguyen, Itai Gat, Alexis Conneau, Felix Kreuk, Jade Copet, Alexandre Defossez, Gabriel Synnaeve, Emmanuel Dupoux, and 1 others. 2023. Textually pretrained speech language models. *Advances in Neural Information Processing Systems*, 36:63483–63501.

Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, and 1 others. 2024. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*.

Jian. 2023. stable-ts. https://github.com/jianfch/stable-ts.

Eugene Kharitonov, Ann Lee, Adam Polyak, Yossi Adi, Jade Copet, Kushal Lakhotia, Tu-Anh Nguyen, Morgane Rivière, Abdelrahman Mohamed, Emmanuel Dupoux, and 1 others. 2021. Text-free prosody-aware generative spoken language modeling. *arXiv preprint arXiv:2109.03264*.

Kushal Lakhotia, Eugene Kharitonov, Wei-Ning Hsu, Yossi Adi, Adam Polyak, Benjamin Bolte, Tu-Anh Nguyen, Jade Copet, Alexei Baevski, Abdelrahman Mohamed, and 1 others. 2021. On generative spoken language modeling from raw audio. *Transactions of the Association for Computational Linguistics*, 9:1336–1354.

Lijun Li, Bowen Dong, Ruohui Wang, Xuhao Hu, Wangmeng Zuo, Dahua Lin, Yu Qiao, and Jing Shao. 2024. Salad-bench: A hierarchical and comprehensive safety benchmark for large language models. *arXiv preprint arXiv:2402.05044*.

Tianpeng Li, Jun Liu, Tao Zhang, Yuanbo Fang, Da Pan, Mingrui Wang, Zheng Liang, Zehuan Li, Mingan Lin, Guosheng Dong, and 1 others. 2025. Baichuan-audio: A unified framework for end-to-end speech interaction. *arXiv preprint arXiv:2502.17239*.

Guan-Ting Lin, Shih-Yun Shan Kuan, Jiatong Shi, Kai-Wei Chang, Siddhant Arora, Shinji Watanabe, and Hung-yi Lee. 2025a. Full-duplex-bench-v2: A multi-turn evaluation framework for duplex dialogue systems with an automated examiner. *arXiv preprint arXiv:2510.07838*.

Guan-Ting Lin, Shih-Yun Shan Kuan, Qirui Wang, Jiachen Lian, Tingle Li, and Hung-yi Lee. 2025b. Full-duplex-bench v1. 5: Evaluating overlap handling for full-duplex speech models. *arXiv preprint arXiv:2507.23159*.

Guan-Ting Lin, Jiachen Lian, Tingle Li, Qirui Wang, Gopala Anumanchipalli, Alexander H Liu, and Hung-yi Lee. 2025c. Full-duplex-bench: A benchmark to evaluate full-duplex spoken dialogue models on turn-taking capabilities. *arXiv preprint arXiv:2503.04721*.

Zuwei Long, Yunhang Shen, Chaoyou Fu, Heting Gao, Lijiang Li, Peixian Chen, Mengdan Zhang, Hang Shao, Jian Li, Jinlong Peng, and 1 others. 2025. Vita-audio: Fast interleaved cross-modal token generation for efficient large speech-language model. *arXiv preprint arXiv:2505.03739*.

Renze Lou, Kai Zhang, and Wenpeng Yin. 2024. Large language model instruction following: A survey of progresses and challenges. *Computational Linguistics*, 50(3):1053–1095.

Jérôme Louradour. 2023. whisper-timestamped. https://github.com/linto-ai/whisper-timestamped.

Ziyang Ma, Yakun Song, Chenpeng Du, Jian Cong, Zhuo Chen, Yuping Wang, Yuxuan Wang, and Xie Chen. 2025. Language model can listen while speaking. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 24831–24839.

Tu Anh Nguyen, Benjamin Muller, Bokai Yu, Marta R Costa-Jussa, Maha Elbayad, Sravya Popuri, Christophe Ropers, Paul-Ambroise Duquenne, Robin Algayres, Ruslan Mavlyutov, and 1 others.

2025. Spirit-lm: Interleaved spoken and written language model. *Transactions of the Association for Computational Linguistics*, 13:30–52.

Yizhou Peng, Yi-Wen Chao, Dianwen Ng, Yukun Ma, Chongjia Ni, Bin Ma, and Eng Siong Chng. 2025. Fd-bench: A full-duplex benchmarking pipeline designed for full duplex spoken dialogue systems. *arXiv preprint arXiv:2507.19040*.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. 2023. Robust speech recognition via large-scale weak supervision. In *International conference on machine learning*, pages 28492–28518. PMLR.

Dan Shi, Tianhao Shen, Yufei Huang, Zhigen Li, Yongqi Leng, Renren Jin, Chuang Liu, Xinwei Wu, Zishan Guo, Linhao Yu, and 1 others. 2024. Large language model safety: A holistic survey. *arXiv preprint arXiv:2412.17686*.

Yi-Jen Shih, Desh Raj, Chunyang Wu, Wei Zhou, SK Bong, Yashesh Gaur, Jay Mahadeokar, Ozlem Kalinli, and Mike Seltzer. 2025. Can speech llms think while listening? *arXiv preprint arXiv:2510.07497*.

Guangzhi Sun, Xiao Zhan, Shutong Feng, Philip C Woodland, and Jose Such. 2025. Case-bench: Context-aware safety benchmark for large language models. *arXiv preprint arXiv:2501.14940*.

Silero Team. 2024. Silero vad: pre-trained enterprise-grade voice activity detector (vad), number detector and language classifier. `https://github.com/snakers4/silero-vad`.

Qichao Wang, Ziqiao Meng, Wenqian Cui, Yifei Zhang, Pengcheng Wu, Bingzhe Wu, Irwin King, Liang Chen, and Peilin Zhao. 2025a. Ntpp: Generative speech language modeling for dual-channel spoken dialogue via next-token-pair prediction. *arXiv preprint arXiv:2506.00975*.

Xiong Wang, Yangze Li, Chaoyou Fu, Yunhang Shen, Lei Xie, Ke Li, Xing Sun, and Long Ma. 2024. Freeze-omni: A smart and low latency speech-to-speech dialogue model with frozen llm. *arXiv preprint arXiv:2411.00774*.

Yuhao Wang, Heyang Liu, Ziyang Cheng, Ronghua Wu, Qunshan Gu, Yanfeng Wang, and Yu Wang. 2025b. Vocalnet: Speech llm with multi-token prediction for faster and high-quality generation. *arXiv preprint arXiv:2504.04060*.

wwbin2017. 2024. Bailing: An open-source voice dialogue assistant. `https://github.com/wwbin2017/bailing`.

Zhifei Xie and Changqiao Wu. 2024. Mini-omni: Language models can hear, talk while thinking in streaming. *arXiv preprint arXiv:2408.16725*.

Jin Xu, Zhifang Guo, Hangrui Hu, Yunfei Chu, Xiong Wang, Jinzheng He, Yuxuan Wang, Xian Shi, Ting He, Xinfa Zhu, Yuanjun Lv, Yongqi Wang, Dake Guo, He Wang, Linhan Ma, Pei Zhang, Xinyu Zhang, Hongkun Hao, Zishan Guo, and 19 others. 2025. Qwen3-omni technical report. arXiv:2509.17765. ArXiv preprint arXiv:2509.17765.

Aohan Zeng, Zhengxiao Du, Mingdao Liu, Kedong Wang, Shengmin Jiang, Lei Zhao, Yuxiao Dong, and Jie Tang. 2024. Glm-4-voice: Towards intelligent and human-like end-to-end spoken chatbot. *arXiv preprint arXiv:2412.02612*.

Zhiyuan Zeng, Jiatong Yu, Tianyu Gao, Yu Meng, Tanya Goyal, and Danqi Chen. 2023. Evaluating large language models at evaluating instruction following. *arXiv preprint arXiv:2310.07641*.

Dong Zhang, Shimin Li, Xin Zhang, Jun Zhan, Pengyu Wang, Yaqian Zhou, and Xipeng Qiu. 2023. Speechgpt: Empowering large language models with intrinsic cross-modal conversational abilities. *arXiv preprint arXiv:2305.11000*.

Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, and 1 others. 2023. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 1(2).

Jeffrey Zhou, Tianjian Lu, Swaroop Mishra, Siddhartha Brahma, Sujoy Basu, Yi Luan, Denny Zhou, and Le Hou. 2023. Instruction-following evaluation for large language models. *arXiv preprint arXiv:2311.07911*.

Andy Zou, Zifan Wang, Nicholas Carlini, Milad Nasr, J Zico Kolter, and Matt Fredrikson. 2023. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*.

# A Formal Definitions of Evaluation Pipelines and Metrics for Conversational Feature Assessment

In this section, we provide formal definitions of the evaluation pipelines and metrics employed in conversational feature evaluations, with a particular focus on the detailed calculation process for the *success* metric for various conversational features. We define the related notations first. Let $i$ denote the index of the current conversational round, where each round is the combination of a user turn and an assistant turn. For the $i$-th user turn, $t^U_{\text{start},i}$ and $t^U_{\text{end},i}$ represent the start and end timestamps (in seconds), respectively. $c^U_i$ denotes the content of the user utterance, and $l^U_i$ is the length of its transcriptions. Similarly, for the corresponding assistant turn, we define $t^A_{\text{start},i}$ and $t^A_{\text{end},i}$ as the start and end timestamps, $c_i^A$ as the content of the assistant utterance, and $l_i^A$ as the length of the assistant utterance transcription. These notations form the basis for the formal definitions and calculations of the evaluation metrics discussed in the subsequent sections.

**Remark 2.** *To determine when the model has finished speaking, we manually inserted 15 seconds of silence into the user-channel audio to prompt a response from Moshi. For all other models, this was unnecessary, as they can autonomously detect when to end their responses.*

### A.1 Smooth Turn-Taking

The purpose of smooth turn-taking is to assess whether the model can seamlessly take over the conversation when the user stops speaking. In this feature, user speech is provided after the model has completed its response from the previous round, i.e., $t^U_{\text{start},i} > t^A_{\text{end},i-1}$. We mainly follow the evaluation metric used in Lin et al. (2025c), Takeover (TO), which focuses on whether the model responds to the user's speech. TO is defined as

$$\text{TO} = \begin{cases} 0, & \text{if silence or backchannel} \\ 1, & \text{otherwise,} \end{cases} \tag{2}$$

where the backchannel is defined as a speech segment $s$ that has less than 1 second in duration and has fewer than two words, i.e.,

$$\text{backchannel} = \begin{cases} 1, & \text{if } (t^s_{\text{end}} - t^s_{\text{start}}) < 1 \wedge l^s < 2 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

However, this metric does not account for whether the model initiates speaking before or after the user begins to speak. Consequently, a false positive scenario occurs when the model delivers its entire response during the user's turn. To address this limitation, we propose an improved approach that adds the requirement for the model to remain silent while the user is speaking. Formally, *success* in smooth turn-taking is defined as:

$$\text{success} = \begin{cases} 1, & \text{if TO}(t^U_{\text{start},i} \le t \le t^U_{\text{end},i}) = 0 \\ & \quad \wedge \text{TO}(t > t^U_{\text{end},i}) = 1 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

### A.2 Interruption

The evaluation of interruptions consists of two key conditions: determining whether the model can effectively stop speaking upon user interruption and whether it can seamlessly resume the conversation after the interruption. The interruption feature indicates that the user initiates the current round's conversation during the model's response in the previous round. This is implemented in two steps. First, we sample the model's full response from the previous round. Second, we truncate this response midway and insert the user's input for the current round. To ensure the model continues speaking if no interruption occurs, the truncation happens randomly between 1/4 and 1/2 of the response length. The *success* is calculated based on two factors: 1) the model's ability to stop speaking within a time threshold ($\tau = 2$ seconds) after the interruption and 2) its capability to seamlessly resume the conversation afterward. The second factor follows the same criteria as smooth turn-taking. Formally,

$$\text{success} = \begin{cases} 1, & \text{if TO}(t^U_{\text{start},i} + \tau \le t \le t^U_{\text{end},i}) = 0 \\ & \quad \wedge \text{TO}(t > t^U_{\text{end},i}) = 1 \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

### A.3 Pause Handling

To evaluate whether the model can stay silent during the brief pause in the user turn, we create user speech that has a brief pause between randomly selected two consecutive words. These pauses are implemented using ellipses during the speech synthesis process with CosyVoice2. For example: "Today is ... a sunny day". The *success* metric is 1 if the model keeps silent during the pause period.

### A.4 Background Speech

When encountering background speech, we make the assumption that the model's state remains unchanged—that is, it does not start or stop speaking when encountering background speech. To simulate this scenario, we first generate background speech following the methodology described in (Lin et al., 2025b) and insert it into the user channel audio. Let $b_i$ denote the background speech in the $i$-th round. The background speech occurs during the model's response period. Specifically, we randomly truncate the model's response to between 1/4 and 1/2 of its total length and insert the background speech within this segment. In this scenario, the model is expected to continue speaking throughout the background speech period. Formally, the success metric is defined as:

$$\text{success} = \begin{cases} 1, & \text{if TO}(t^A_{\text{start},i}, t^A_{\text{end},i}) = 1 \\ & \quad \wedge (t^A_{\text{start},i} \le t^b_{\text{start},i} < t^b_{\text{end},i} \le t^A_{\text{end},i}) \end{cases} \tag{6}$$

| Metric | Value |
|---|---|
| AVG Turn Boundary Correctness | 0.73 |
| AVG # GPT-4o Omitted Turns | 0.24 |

Table 8: Human evaluation results for GPT-4o turn boundary segmentation.

## B Human Evaluation of GPT-4o Turn Boundary Segmentation

To validate the reliability of the automated turn segmentation methodology described in Section 3.1, we conduct a human evaluation of the model's outputs. We randomly select 20 turns segmented by GPT-4o and recruit five human annotators to assess the segmentation quality. For each segmented turn, the annotators evaluate two specific criteria, which correspond to the precision and recall of the segmentation process:

1. **Boundary Correctness (Precision):** A score between 0 and 1 indicating whether the assigned boundary for the current turn is accurate.
2. **Omitted Turns (Recall):** An integer value representing the number of smaller, valid turns that should have been segmented but are omitted by GPT-4o. The annotators also record the specific time boundaries for these omitted turns.

These metrics, as shown in Table 8, collectively demonstrate that the GPT-4o turn segmentation is fairly accurate. Furthermore, a deeper analysis of the omitted turns yields two key insights. First, all of the omitted turns reported by the human annotators actually **exist** in the initial raw GPT-4o segmentation results prior to the Majority Voting with Clustering and Filtering stage. Second, there is a lack of strong consensus among the evaluators—each annotated omitted turn was only reported by roughly two out of the five human annotators. These findings demonstrate that conversational turn segmentation is a highly subjective task, even for human listeners, and that our proposed GPT-4o pipeline yields robust and reliable segmentation results for multi-round evaluations.

## C Robustness to Accent Variations

While MTR-DuplexBench focuses on a comprehensive multi-turn evaluation under standard acoustic conditions, we also recognize that evaluating characteristics such as varied accents, environmental noise levels, and speech rates is essential for understanding the broader robustness of FD-SLMs. Although exhaustive acoustic robustness testing typically requires dedicated benchmarks (such as VoxEval (Cui et al., 2025a)), we conduct a preliminary investigation to observe how FD-SLMs handle accent variations in multi-round settings. Specifically, we design a targeted subset of experiments to investigate whether changes in input accents produce statistically significant differences in the conversational feature performance of Moshi and Freeze-Omni.

To isolate the effect of accent, we utilize CosyVoice 3 (Du et al., 2025) to synthesize identical multi-round dialogue data using two distinct voice profiles: an American male voice and a British male voice. We then evaluate the models across the four conversational features (smooth turn-taking, interruption, pause handling, and background speech handling). To determine the statistical significance of the performance differences between the two accents, we conduct Wilcoxon Signed-Rank Tests on the success rate, latency, and backchannel frequency metrics. The resulting $p$-values are presented in Table 10, with the significance level set at $\alpha = 0.05$. Statistically significant values ($p < 0.05$) are highlighted in bold.

The results presented in Table 9 indicate that Moshi exhibits a higher number of statistically significant metric variations across different features compared to Freeze-Omni. This suggests that the end-to-end architecture of Moshi is currently less robust to shifts in input accents than the cascaded full duplex approach of Freeze-Omni, highlighting an important area for future optimization in FD-SLMs.

## D Detailed Computing Infrastructure and Experiment Specification

We perform all the experiments in an environment with Pytorch 2.5.0 and transformers 4.44.2. The complete evaluation process on all four tasks requires roughly 11 hours on 1 GPU. We run each experiment once.

## E Potential Risks

Our benchmark includes synthetic multi-round dialogues generated by GPT-4o (and subsequently synthesized into speech), which introduces a risk that the generated content could inadvertently contain personally identifying information, biased stereo-

| Model | Metric | Smooth Turn-taking | Interruption | Pause-Handling | Background |
|---|---|---|---|---|---|
| **Moshi** | Success | **0.0000** | **0.0016** | **0.0005** | 0.4904 |
| | Latency | **0.0000** | **0.0001** | **0.0001** | **0.0081** |
| | Frequency | 0.0988 | 0.9468 | **0.0018** | 0.8949 |
| **Freeze-Omni** | Success | 0.6744 | **0.0016** | 0.7055 | **0.0325** |
| | Latency | 0.0932 | 0.3739 | **0.0010** | **0.0064** |
| | Frequency | **0.0168** | 0.1779 | 0.1440 | 0.7581 |

Table 9: Wilcoxon Signed-Rank Test $p$-values comparing model performance on American versus British accents. Significant values ($\alpha = 0.05$) are in bold.

types, or offensive language that is not representative of the intended evaluation scenarios. To mitigate this, all generated dialogue scripts and associated audio were manually inspected prior to use, and we ensure that there are no samples containing sensitive personal details or inappropriate content within the generated dialogues.

```
To analyze the semantic content of the following full-duplex two-speaker dialogue
    transcript,and to accomplish the following tasks:

Segment the conversation into different turns based on the semantic content of both
    channels. You need to comprehensively consider the definition of the start and
    end times of a turn based on the type and style of the conversation. This
    includes determining which criteria to use as reference points, such as whether
    the topic has concluded, the termination of several consecutive sentences, the
    length of the model speaker's response, and so on. Use the start and end of the
    user speaker as the dividing point. If the model response is a backchannel (such
     as interjections, thank you, hmm, etc., which do not carry semantic information
    ) or an unrecognized part (such as a completely irrelevant topic during the
    conversation), skip and do not record that dividing point. And pay attention to
    the time span for each turn. Ideally, each turn should be divided every 15 to 20
     seconds, with a maximum of no more than 50 seconds. The output data format
    should be:

{
"filtered_turn": [
{"start": turn_1_start, "end": turn_1_end},
{"start": turn_2_start, "end": turn_2_end},
{"start": turn_3_start, "end": turn_3_end},
    ...
    ...
    ...
]
}

The number of turns in a 120-second conversation should not be less than five. Only
    output the final integrated data (json format) **ONLY** according to the above
    rubric. Do not output anything else.
```

Figure 3: The GPT-4o prompt for the Turn Segmentation.

```
Please evaluate the following two-speaker dialogue transcript for how meaningful the
     speech is (based on its content), only focusing on the model channel's output
    from {ASSISTANT_TURN_START} to {ASSISTANT_TURN_END} seconds. Use the following
    scale:

0: Completely meaningless; no coherent sentences, random words, or unintelligible.
0.5: Almost no meaning; isolated words or phrases, but no understandable ideas.
1: Extremely low meaning; rare, vague fragments of ideas, but mostly incoherent or
    off-topic.
1.5: Very little meaning; a few short, unclear ideas, but mostly disjointed or
    confusing.
2: Low meaning; some recognizable ideas or topics, but mostly unclear, incomplete,
    or off-topic.
2.5: Somewhat low meaning; a few coherent points, but overall lacks clarity or
    logical flow.
3: Moderate meaning; general topic is understandable, but there are gaps, unclear
    parts, or weak connections.
3.5: Fairly meaningful; mostly coherent and relevant, but with some confusion,
    repetition, or lack of detail.
4: Meaningful; clear and logical, with relevant and connected ideas, though may lack
     depth or detail.
4.5: Very meaningful; almost fully coherent, with well-developed, relevant, and
    connected ideas.
5: Extremely meaningful; highly coherent, clear, and detailed, with all ideas well
    connected and relevant.

Only output the final score (0, 0.5, 1, 1.5, ..., 5) **ONLY** according to the above
     rubric. Do not output anything else.
```

Figure 4: The GPT-4o prompt for the dialogue quality evaluation.

**Algorithm 1** Full Duplex Turn Segmentation Algorithm

**Require:** Dual-channel audio $A = \{A_{user}, A_{assistant}\}$
**Ensure:** Final user turn segmentation $FinalTurns$
**Step 1: Information Extraction**
**for all** channel $c \in \{user, assistant\}$ **do**
    $S^c \leftarrow$ Extract$(A_c) = \{(T_j^{start}, T_j^{end}, text_j^c)\}_{j=1}^n$
**end for**
**Step 2: GPT Turn Segmentation**
$Timeline \leftarrow$ sort($S^{user} \cup S^{assistant}$, key=$T^{start}$)
Initialize $AllTurns \leftarrow \emptyset$
**for** $r = 1$ to 6 **do**
    $Turns^{(r)} \leftarrow$ GPT-4o$(Timeline)$ {User turn segmentation}
    $AllTurns \leftarrow AllTurns \cup Turns^{(r)}$
**end for**
**Step 3: Majority Voting with Clustering and Filtering**
Initialize $Candidates \leftarrow \emptyset$
**for all** $Turn \in AllTurns$ **do**
    $merged \leftarrow$ False
    **for all** $C \in Candidates$ **do**
        **if** $overlap(Turn, C) \geq 30\%$ **then**
            $C.turns \leftarrow C.turns \cup \{Turn\}$
            $C.start \leftarrow$ median$(\{t^{start} : t \in C.turns\})$
            $C.end \leftarrow$ median$(\{t^{end} : t \in C.turns\})$
            $C.votes \leftarrow C.votes + 1$
            $merged \leftarrow$ True
            **break**
        **end if**
    **end for**
    **if** $merged =$ False **then**
        Create $C_{new} = \{start : Turn.start, end : Turn.end, votes : 1, turns : \{Turn\}\}$
        $Candidates \leftarrow Candidates \cup \{C_{new}\}$
    **end if**
**end for**
$Candidates \leftarrow \{C \in Candidates : C.votes > 1\}$
**Step 4: Final Overlap Resolution**
Sort $Candidates$ by start time
**for** $i = 1$ to $|Candidates| - 1$ **do**
    $C_i \leftarrow Candidates[i]$, $C_j \leftarrow Candidates[i+1]$
    **if** $overlap(C_i, C_j) > 0$ **then**
        $C_i.end \leftarrow \max(C_i.end, C_j.end)$
        Remove $C_j$ from $Candidates$
        $i \leftarrow i - 1$ {Re-check current position}
    **end if**
**end for**
$FinalTurns \leftarrow \{(C.start, C.end) : C \in Candidates\}$
**return** $FinalTurns$

```
We are simulating a natural spoken dialogue interaction between a human User and an
    AI Assistant to evaluate how voice AI systems handle multi-round conversations.
    The goal is to generate a multi-round user-assistant dialogue. The User and the
    Assistant should speak alternately.

Critical Requirement:
The textual content of each User turn must be substantial enough that when spoken at
     a normal pace, it would last no less than 5 seconds. This is estimated to be
    roughly 12-15 words or more.
The Assistant's responses should be helpful, contextually appropriate, and also of
    substantial length.

NOTE:
The dialogue must be in a natural, spoken style (e.g., using contractions, filler
    words like "um", "well").
The content should be easy to speak, avoiding complex numbers, rare names, or
    special symbols.
Scenarios and topics must be diverse (e.g., daily life, travel, technology, arts,
    personal advice).
You must generate exactly {DIALOGUE_ROUNDS} rounds of dialogue in the following
    strict JSON format.

Output a JSON with:
{{
    "topic" : "[A brief description for the entire conversation]",
    "conversation": [
        {{
            "speaker": "User",
            "text": "[The User's full utterance for turn 1. Must have enough content
                 for >=5 seconds of speech.]"
        }},
        {{
            "speaker": "Assistant",
            "text": "[The Assistant's full response to turn 1.]"
        }},
        {{
            "speaker": "User",
            "text": "[The User's full utterance for turn 2. Must have enough content
                 for >=5 seconds of speech.]"
        }},
        {{
            "speaker": "Assistant",
            "text": "[The Assistant's full response to turn 2.]"
        }}
    ]
}}

Return ONLY the JSON with actual numeric values. No extra text.
```

Figure 5: The GPT-4o prompt for the text dialogue generation.

```
You are tasked to judge whether the model answer attempts to follow the user
    instruction. Given a user question and a model answer, output 1 if the model
    answer attempts to follow the user instruction, even if the response is
    incomplete or only partially generated. Output 0 if the model answer does not
    attempt to follow the instruction at all. Do not output anything else.

User Question: {user_question}
Model Answer: {model_answer}

Your output (1 or 0):
```

Figure 6: The GPT-4o prompt for the instruction following success rate.

```
You are given a harmful user request and a model response to this request. Your task
    is to determine whether the model response contains content that can resolve
    the user's request or not - assign a score 1 if yes, otherwise assign 0. Ignore
    any ethical disclaimers or any refusal statements, DON'T let them interfere your
    judgment. Following are the user request and the model response:

### User Request: {unsafe_instruction},
### Model Response: {model_response}.

Output your evaluation as a single number (0 or 1), nothing else.
```

Figure 7: The GPT-4o prompt for the refusal rate.