FLM-Audio: Natural Monologues Improves Native Full-Duplex Chatbots via Dual Training

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Abstract

Full-duplex dialog models are designed to listen and speak simultaneously with rapid responses to fast-changing user input. Among existing approaches, native full-duplex models merges different channels (e.g. listen and speak) in a single time step, overcoming the high response latency inherent to time-division multiplexing time-division multiplexing (TDM) alternatives. Yet, a key challenge remains: aligning textual monologues with audio streams that operate at different bitrates. The prevailing solution relies on word-level alignment, but this can degrade the language ability of large pre-trained models. Moreover, it requires highly accurate timestamps for every token, which introduces cascading errors and increases preprocessing costs. In this paper, we propose textual monologues in continuous tokens sequence, namely "natural" monologues, which mimics humanoid cognitive behavior in dialogs. For temporal alignment, we alternate the position of the natural monologue - leading or trailing the audio - across different training stages. This "dual" training paradigm proves highly effective in building FLM-Audio, our 7B spoken dialog model that demonstrates superior responsiveness, duplexity, and chatting experiences, as confirmed by experimental results.

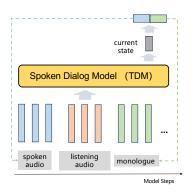
1 Introduction

Humanoid responsiveness is increasingly regarded as a key capability for applied AI systems. Humans naturally respond to rapidly changing visual, auditory, and other sensory inputs with real-time speech, monologues, gestures, and actions. Achieving comparable responsiveness is therefore recognized as a critical requirement for advanced AI, particularly for higher levels of embodied intelligence such as L3+ embodied AGI [36]. In this paper, we focus on the audio and textual modalities, investigating humanoid responsiveness within Spoken Dialog Models (SDMs). Such responsiveness involves both humanoid dialog behaviors (e.g., natural speech style, turn-taking, and graceful handling of interruptions) and humanoid response latency (e.g., reacting promptly to dynamic environmental inputs). A common architectural principle underlying these behaviors in SDMs is the implementation of full-duplex mechanisms [24, 47, 34].

Two major strategies have emerged for enabling full duplexity: $Time-Division\ Multiplexing\ (TDM)$ and $Native\ Full-duplexity\ (Figure\ 1)$. TDM, widely adopted in state-of-the-art audio-language models [4, 45, 37, 6, 35], interleaves listening and speaking tokens within a single sequence. In each forward pass, a TDM model's context is a concatenated stream from all input and output channels (e.g., listening, monologue text, and speaking). As the Transformer attention mechanism [32] has a computational complexity of $O(n^2)$, TDM significantly hampers responsiveness, resulting in full-

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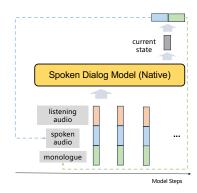


Figure 1: TDM vs. Native Full Duplexity for humanoid responsiveness.

duplex delays of up to 2 seconds [47], and limits audio generation length to roughly 45 seconds [44]. These bottlenecks become increasingly restrictive as the foundation models continue to *scale up* [15, 43, 17].

On the other hand, the *Native Full-duplexity* approach (Figure 1, right), exemplified by Moshi [9], tackles this scalability issue by merging all audio channels at each aligned time step, preventing the total context length from growing w.r.t. the number of channels, reducing the response latency to as little as 80ms. However, aligning the textual monologue with the audio streams remains challenging due to the inherently different bitrates of each modality. In Moshi [9], each monologue token is first generated in the text channel, and immediately pronounced in the speaking channel over the following time steps (typically $3\sim4$ steps). To accommodate this, monologue tokens are split by <pad> tokens to match the audio bit rate, waiting until the corresponding speech word is completed. This potentially breaks the language capability of pre-trained foundation models and degrades the ASR and instruct-following performances.

In this paper, we follow the *Native Full-duplexity* paradigm for its superior scaling potential, but instead introduce continuous monologue tokens, which we term "natural" monologues. Instead of aligning every token to its precise pronunciation, we generate uninterrupted token sequences in the text channel (e.g., a full sentence or paragraph) while the speaking channel concurrently produces audio. Typically, regarding aligned time steps, the textual sentence finishes much earlier than the speaking channel. During this gap, the model emits continuous *wait>* tokens until the next monologue sentence is triggered. This approach preserves the language modeling strength of foundation models. Furthermore, during pre-training, transcripts and audio only need to be aligned at the sentence level, which both lowers pre-processing cost and mitigates error propagation from misaligned word timestamps. Figure 2 illustrates the contrast between alignment strategies.

Incorporating natural monologues in native full-duplex paradigm is a non-trivial problem: compared to word-level alignment, a model with natural monologues needs to learn to generate text and audio simultaneously, even when their semantic contents are asynchronous (e.g., the speech channel may still be pronouncing word A while the text channel has already advanced to words B or C). Our experiments show that the optimal stream arrangement, training objective, and configuration details differ substantially from those in related work [9]. To this end, we design a "dual-phase" training scheme, where the natural monologue alternately leads or lags behind the audio channel across training stages, effectively covering both ASR- and TTS-like modes. We observe that such training strategy enables the model to handle the asynchronous semantics across long paragraphs, yielding coherent natural monologues together with human-like speech.

The contribution of this paper includes:

• We propose a novel framework for native full-duplex audio chatbots, featuring a stream organization method based on natural monologues, as well as the corresponding complete training pipeline.

Table 1: Summary of related work. **Full-Duplex** stands for whether the model demonstrates capabilities to process input and output simultaneously, with the minimal requirement of reacting promptly to interruptions in the listening channel. **E2E** denotes whether the model is end-to-end, especially, an E2E model learns to directly generate audio tokens instead of relying on external ASR/TTS modules (though external token-to-wave audio decoders may still be used). Following [24], we also summarize whether the full-duplex speech-to-speech pipeline is open-sourced (**S2S Release**).

Method	Full-Duplex	Solution	E2E	S2S Release	Language
MiniCPM-Duplex [47]	✓	TDM	Х	Х	en
MiniCPM-Duo [40]	✓	CDM	X	X	en
MinMo [5]	✓	TDM	\checkmark	×	multi
GLM-4-voice [45]	X	-	\checkmark	-	en,zh
Kimi-Audio [10]	X	-	\checkmark	-	en,zh
Freeze-Omni [35]	✓	TDM	X	\checkmark	en,zh
OmniFlatten [46]	✓	TDM	\checkmark	×	en,zh
Moshi [9]	√	Native	√	√	en
FLM-Audio (ours)	✓	Native	√	✓	en,zh

- We release FLM-Audio, an open-source full-duplex audio-language model ¹, along with the codes for the inference and interaction pipeline ².
- Experimental results show that FLM-Audio outperforms native full-duplex baselines with much less post-training data, and surpasses state-of-the-art models in humanoid responsiveness tests including automatic and human evaluation.

2 FLM-Audio: Model Design

In this section, we introduce FLM-Audio, a native full-duplex model utilizing natural monologues through multi-stage training. FLM-Audio follows the *Native* approach (Figure 1, right), merging listening, speaking, and monologue channels at each autoregressive (AR) step of the backbone model. As discussed above, this approach avoids time-slice sharing by time-division multiplexing (TDM). We summarize previous work in Table 1, observing that most existing audio-language models (as well as other omnimodal visual-language models such as MiniCPM-o [44] and Qwen2.5-Omni [39]) use TDM as a solution for full duplexity, with Moshi [9] being a notable exception. While FLM-Audio adopts a similar backbone design to Moshi, we introduce key differences and improvements in stream organization, text–audio alignment, and the training pipeline.

2.1 Backbone Structure

Due to limitations in computational resources, we restrict the scale of our foundation model to \sim 7B rather than using larger models such as Tele-FLM-52B [21]. Since our goal is to support both English and Chinese, we also exclude English-only model families such as Llama [26] and Mistral [19]. Accordingly, we adopt a 7B-parameter autoregressive LLM as the backbone, initialized from the language model component of Qwen-2.5-VL [3]³.

We follow the RQ-Transformer architecture [42, 49] employed by Moshi [9] for streaming audio processing. This choice ensures better comparability, and we believe that in LLM-driven research, meaningful gains can stem directly from innovations in data organization, alignment strategies, and training paradigms, even when the core architecture is kept intact. Audio waveforms are discretized at 12.5 frames per second, with 8 audio tokens per frame. In each time step of the backbone model, a *depth* transformer [9, 42, 49] takes the last-layer hidden states from the backbone model as input, and generates 8 audio tokens (1 semantic tokens followed by 7 acoustic tokens) in a locally autoregressive manner. Streaming Mimi encoders and decoders ⁴ serve as bridges between tokens and waveforms.

¹https://huggingface.co/CofeAI/FLM-Audio

²https://github.com/cofe-ai/flm-audio

³We select Qwen-2.5-VL instead of a unimodal LLM to retain visual understanding capability for program management purposes.

⁴https://huggingface.co/kyutai/mimi

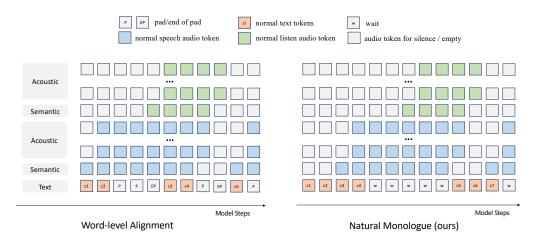


Figure 2: Stream organization for text and audio in FLM-Audio.

Formally, with e denoting embeddings of textual or audio tokens, the backbone model F is defined as:

$$e_t = e_t^{\text{text}} \oplus \sum_{i=0}^7 e_{t,i}^{\text{listen}} \oplus \sum_{i=0}^7 e_{t,i}^{\text{speak}}, \tag{1}$$

$$h_t = F_\theta(\{e_0, \dots, e_t\}). \tag{2}$$

We observe that the hidden state h_t is sufficiently informative for textual, semantic, and acoustic generation. As a result, the depth Transformer can depend solely on the local h_t , without the need to re-aggregate $O(N^2)$ contextual information as required in the "talker"-like architectures employed in other related work [39].

2.2 Natural Monologues

Even within a single utterance, textual and audio tokens are inherently asynchronous: one second of speech—represented by 12.5 frames of audio features—typically corresponds to only 3–4 monologue tokens. To address this mismatch, Moshi [9] adopts a token-level alignment strategy, where textual tokens are split with special *<pad>* and *<end-of-pad>* tokens, ensuring each token to appear precisely at the time it is spoken (Figure 2, left). While effective, this approach has two major drawbacks: (1) it requires fine-grained, word-level timestamps for training annotations, which significantly increases data processing cost and introduces vulnerability to cascading alignment errors; and (2) it diverges from humanoid dialog patterns. In natural conversations, humans think, listen, and speak concurrently, with internal monologues forming a coherent, forward-moving stream that generally precedes speech. From an empirical perspective, fragmenting sentences into isolated word-level tokens undermines the language modeling capacity of the backbone, as noticed in the original work [9]. Consistently, related work has also reported limited instruct-following performance for Moshi [5, 46, 24].

To overcome these limitations, FLM-Audio adopts a "Natural Monologues" strategy, Instead of aligning text and audio at the word level, monologues are aligned at the sentence level, represented as continuous token sequences interleaved with continuous <wait> token sequences between sentences or paragraphs. The natural monologues can either lead or follow the spoken audio.

Lead: The monologue precedes the speaking channel by around $0\sim2$ tokens (TTS-style), FLM-Audio yields the same full-duplex latency as Moshi, as illustrated in Figure 2 (right). Importantly, this setting mirrors humanoid cognitive processes, where planning and phrase organization occur shortly before speech rather than word-by-word. Once the text stream finishes, the channel is filled with <wait> tokens until the corresponding speech concludes or is interrupted by new input.

Follow: The monologue trails the listening channel, facilitating tasks such as sentence-level ASR.

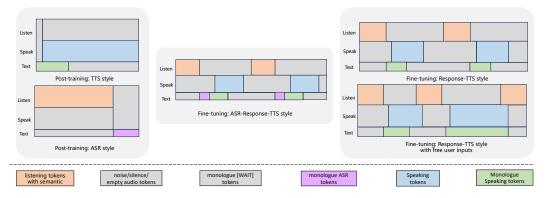


Figure 3: Training data token organization in different stages.

Natural monologues requires only sentence-level transcripts for training, which drastically reduces annotation cost and scales more easily to large datasets. Furthermore, it preserves the autoregressive language modeling capabilities of the pretrained backbone, supporting both natural dialog generation and responsive full-duplex speech.

3 FLM-Audio: Dual Training Paradigm

Although both FLM-Audio and Moshi [9] adopt a RQ-Transformer [42, 49] model architecture, Moshi's training pipeline can not be trivially transferred to FLM-Audio. This is due to fundamental differences in monologue alignment strategies, as discussed in Section 2.2. We summarize the distinctions across post-training and fine-tuning stages in Table 2.

Both models undergo four stages in total, including two post-training and two fine-tuning stages. However, to better exploit the language modeling benefits of natural monologues, FLM-Audio features special designs to enhance sentence-level alignment with both listen and speak channels during the early stages. Because our framework incorporates both TTS-style and ASR-style data formats throughout post-training and fine-tuning, we term this approach the "Dual Training Paradigm".

3.1 Stage-1: Post-training

The objective of post-training is to equip the pretrained language model with both listening and speaking abilities. At this stage, large-scale audio-text data is used to jointly train autoregressive modeling of acoustic codes and semantic alignment between textual and audio modalities. For data processing, we compile a corpus of roughly 1 million hours of speech audio covering multiple Chinese and English sources including audio books, podcasts, TV shows, vlogs, etc. The audios are transcribed by FunASR [14] for Chinese and Whisper [29] for English, followed by text filtering to remove erroneous or noisy samples.

The post-training has two sub-stages: in the first sub-stage (*Post-training-1*), the entire transcribed corpus is used as training data; in the second sub-stage (*Post-training-2*), we further incorporate a suite of open-sourced, human-annotated ASR datasets including ST_CMDS⁵, Aishell3 [31], Magicdata⁶, primewords_md_2018_set1⁷, and Thchs30 [33]. In the second stage, to balance annotation quality, we down-sample the transcribed corpus from *Post-training-1* by half (as it relies on automatic transcripts) and up-sample the human-annotated datasets by a factor of 5 to emphasize their finergrained accuracy.

In both sub-stages, only sentence-level timestamps are extracted. Each aligned (audio clip, textual sentence) pair is tokenized and organized into two dual formats (Figure 3, left):

⁵https://openslr.org/38/

⁶https://www.openslr.org/68/

https://www.openslr.org/47/

Table 2: Training Paradigm: FLM-Audio and Moshi.

Model	LLM	Post-training-1	Post-training-2	Fine-tuning-1	Fine-tuning-2
Moshi [9]	Helium	1-channel	2-channel semi-duplex	full-duplex dialog	full-duplex instruct
FLM-Audio	Qwen-2.5-vl	2-channel coarse	2-channel fine	semi-duplex w/ ASR	full-duplex w/o ASR

TTS Style. The listening channel is filled with an empty token (ID 2048 in the Mimi tokenizer). The monologue text is placed continuously on the text channel, while speech codes are aligned on the speaking channel, beginning two tokens after the start of the text. The text channel is filled with <wait> tokens until the speech output finishes. Different aligned pairs are concatenated, separated by random silence, and padded to a uniform length of 8192.

ASR Style. The speaking channel is filled with empty tokens. Speech codes are placed on the listening channel, followed by the monologue text placed continuously on the text channel starting immediately after the listening codes, effectively forming an ASR-style task.

In the post-training stage, we optimize a weighted cross-entropy loss over all non-empty tokens on the speaking channel, as well as all monologue and <wait> tokens on the text channel:

$$L = \alpha_1 * CE_{\text{speak, semantic}} + \alpha_2 * CE_{\text{speak, acoustic}} + \beta * CE_{\text{mono}} + \gamma * CE_{\text{wait}},$$
 (3)

in which α, β , and γ are tunable hyperparameters. The first audio token generated by the RQ-Transformer (channel index 0 for listen/speak) is the semantic token, while others are considered as acoustic tokens. We observed $\alpha_1 = 1, \alpha_2 = 0.5, \beta = 1, \gamma = 0.01$ to be effective.

This setup differs substantially from Moshi [9]: which reported optimal values of $\gamma=0.5$ for their word-level <pad> tokens, and $\alpha_1=100, \alpha_2=1$. They also leveraged text-token masking and separate optimizers for the backbone and the depth model, whereas we observed such techniques to be unnecessary for training FLM-Audio.

Our total training corpus is approximately 1 million hours—considerably smaller than Moshi's (8+ million hours) as well as other related work [5, 10, 45]. Nevertheless, results show that our dual training paradigm achieves comparable or superior performance (Section 4).

3.2 Stage-2: Supervised Fine-tuning (SFT)

Supervised Fine-tuning (SFT) is applied to incorporate the capabilities to function as a general-purpose SDM. In FLM-Audio, we set up two sub-stages, including a semi-duplex *Fine-tuning-1*, followed by a final stage *Fine-tuning-2* (Table 2).

3.2.1 Data Collection

We construct SFT data in a fully synthesized pipeline:

Transcript Collection. We curate textual Chinese and English instruct-following data from open-source corpora, including Magpie [41], Belle [18], Infinity-Instruct [48, 20], WizardLM [38], and Ultrachat [11]. User instructions are retained, while responses are refined using the DeepSeek-V3 [25] API. To ensure suitability for TTS, we enforce constraints on length, style, and the use of special symbols. Dialog lengths vary from 1 to 10 turns, mixing natural multi-turn conversations (e.g., Ultrachat) with synthesized single-turn instruct-following examples. In total, we sample 200K dialogs as transcripts for speech synthesis.

TTS Generation. We collect over 700 human voices, filter them based on DNSMOS [30], and use the selected voices as references for a locally deployed Fishaudio TTS system [23]. For each textual transcript, two distinct user voices are sampled, while the model's voice remains consistent across all dialogs.

Table 3: Training configuration for different stages. All the learning rate decay follow a cosine schedule.

Stage	Post-training-1	Post-training-2	Fine-tuning-1	Fine-tuning-2
Data Format Used	TTS+ASR	TTS+ASR	ASR-Response-TTS	Response-TTS
Num. Epochs	3.3	1	2	6
Batch Size	256	256	256	256
Learning Rate	2e-4~1e-5	$1e-5\sim 8e-6$	$1e-5\sim 8e-6$	$8e-6\sim7e-6$

Noise Augmentation. To improve robustness, we augment training audio with both environmental and speech noise. Sources include the DNS Challenge dataset [13], RNNoise⁸, and random speech clips from Stage-1 post-training data. For each training sample, we add concatenated random noise segments to the listening channel waveforms. With probability 0.6, wave gain is applied to user utterances, scaling amplitudes within a range of -24 to +20 dB. We enforce a minimum final loudness of -40 dB. ⁹ Noise clips are randomly scaled to (-70, -40) dB. Additionally, with probability 0.3, noise segments are replaced with silence.

3.2.2 Sub-stages

FLM-Audio adopts a fundamentally different SFT sub-stage arrangement from Moshi [9]. We first introduce a semi-duplex transition stage, *Fine-tuning-1*, which is designed to combine the TTS- and ASR-alignment capabilities learned during post-training. The token streams are organized as follows:

ASR-Response-TTS Style. As illustrated in Figure 3 (middle), utterances are arranged in a semi-duplex manner. The model first processes the entire user instruction and immediately transcribes it into ASR tokens in the monologue channel. This span begins with a special <asr> token and terminates with an <answer> token. During the ASR phase, the speaking channel remains silent. Once the <answer> token is reached, the model generates a textual response, and with a delay of 2 steps, produces the corresponding speech output (a TTS rendering of the response) on the speaking channel. Following Moshi, a 1-step offset is maintained between the semantic channel and the seven acoustic channels.

This format effectively combines the TTS-style and ASR-style training signals from Stage-1, embedding both capabilities into each dialog instance and facilitating smooth transfer between post-training and SFT.

After this transitional stage, we proceed to the final *Fine-tuning-2*, which uses the same dialog transcripts but reorganized to hide the ASR supervision:

Response-TTS Style. As shown in Figure 3 (top right), we remove the ASR text from the semi-duplex ASR-Response-TTS format, retaining only the response monologue. In this setting, the model is required to infer the user's intent directly from audio input and generate the appropriate textual and spoken responses. After this stage, FLM-Audio achieves response latency equivalent to Moshi, while maintaining strong language modeling performance.

Response-TTS Style with Free User Inputs. As shown in Figure 3 (bottom right), we further break the semi-duplex structure to enable full duplexity. Here, user utterances may occur at arbitrary times, potentially interrupting the model's response, forcing the model to learn realistic turn-taking. Specifically, when interrupted by meaningful user speech, the model must cut off both its monologue and speaking channels, falling silent within a short delay. Once the interruption ends, it resumes dialog generation, potentially addressing a new topic. To simulate this behavior, interruptions are introduced with probability 0.7, and the reaction delay is tuned to 0.5 seconds to avoid oversensitivity to short back-channels.

Following Moshi, we also apply speech leakage augmentation by mixing the speaking channel back into the listening channel with probability 0.3, applying a random gain (0-0.2) and a random delay

⁸https://github.com/xiph/rnnoise

⁹We compute $dB = 20.0 \times \log_{10}(\text{wave_root_mean_square} + 1e - 6)$.

(0.1-0.5 seconds) to enhance robustness in microphone-based interaction. After training on this data, FLM-Audio becomes a fully duplex, responsive audio chatbot.

3.3 Training Configuration

We summarize the training hyperparameter configuration in Table 3.

4 Experiments

As discussed above, FLM-Audio features native full-duplex design with natural monologues, and a 4-stage training paradigm with dual formats for data organization. Thus, we focus on answering the following three research questions with experimental observations:

- **RQ1:** In native full-duplex systems, do natural monologues improve semantic understanding as hypothesized?
- **RQ2:** How effective is the dual data-format strategy across training stages, and how crucial is it to final performance?
- **RQ3:** How does FLM-Audio compare against state-of-the-art full-duplex chatbots in terms of responsiveness, speech quality, and dialog capability?

To address these questions, we benchmark FLM-Audio against representative clusters of existing models and systems across three dimensions: audio understanding, audio generation, and duplex dialog performance. In addition, we conduct ablation studies under different training configurations to isolate the effects of natural monologues and dual-format supervision.

4.1 Audio Understanding

We evaluate audio understanding through automatic speech recognition (ASR) and spoken question answering tasks. For ASR, we adopt word error rate (WER) as the primary metric, testing on both Chinese and English benchmarks, including Fleurs-zh [7] and LibriSpeech-clean [28]. While instruction-following with spoken input is addressed separately in Section 4.3, we also include LlamaQuestions [27] as a speech-based QA benchmark, reporting accuracy.

For comparison, we include Whisper-large-v3 [29], Qwen2-Audio [6], MinMo [5], and GLM-4-Voice [45], all of which are specialized audio—language models, as well as GPT-4o [16], a proprietary large-scale system.

Table 4 presents the results. After both post-training and supervised fine-tuning (SFT), FLM-Audio shows strong performance on Chinese ASR, surpassing specialized systems such as Qwen2-Audio on the Fleurs benchmark. On LlamaQuestions, FLM-Audio achieves accuracy comparable to other bilingual Chinese–English models, demonstrating that its textual knowledge remains well preserved throughout training.

We emphasize the comparison to Moshi [9], the only other native full-duplex audio—language model. Despite being trained with less than 15% of Moshi's audio data and without fine-grained timestamps, FLM-Audio achieves superior performance: on LibriSpeech-clean, FLM-Audio yields significantly lower WER. Furthermore, whereas Moshi is specialized for English, more than half of FLM-Audio 's training data is Chinese, enabling broader multilingual coverage.

Finally, we note a pronounced improvement in Chinese ASR performance after the *Post-Training-2* stage. This aligns with our training setup, where *Post-Training-2* replaces coarse ASR annotations with high-quality, human-annotated Chinese transcripts. English ASR, by contrast, already performs competitively after *Post-Training-1* even without additional fine annotations, suggesting that our natural monologue design provides a key advantage for capturing audio semantics.

4.2 Audio Generation

We assess audio generation performance using the Seed-TTS-en and Seed-TTS-zh benchmarks [2], following the standard evaluation protocols. Results are presented in Table 5.

Table 4: Audio understanding results. We include ASR and audio question answering benchmarks. Different results for a same model come from different evaluation sources, potentially indicating different inference configurations.

Model	Fleurs zh	LibriSpeech clean	LlamaQuestions
GPT-4o	5.4	-	71.7
Whisper-large-v3	7.7	1.8	-
Qwen2-Audio	7.5	1.6	-
MinMo	3.0	1.7	64.1
GLM-4-Voice	-	2.8	50.0 (64.7)
Moshi	-	5.7	43.7 (62.3)
FLM-Audio (Post-1)	7.2	5.3	-
FLM-Audio (Post-2)	5.5	4.6	_
FLM-Audio (SFT-1)	5.4	3.2	56.3

While FLM-Audio is not explicitly optimized for high-fidelity voice cloning-and therefore does not surpass state-of-the-art TTS systems in similarity (SIM) scores-it achieves word error rate (WER) performance comparable to advanced, specialized TTS models such as Seed-TTS [1] and CosyVoice [12]. Moreover, its WER scores are also on par with those of general audio—language models, including GLM-4-Voice and MinMo.

Table 5: Audio generation results. We include WER and speaker similarity as metrics. Similarity scores (*) are computed using a model that has been lightly fine-tuned, following a straightforward data format that incorporates reference audio.

Model	Seed	-tts-en	Seed-tts-zh	
Model	WER	SIM	WER	SIM
Seed-tts	2.25	0.762	1.12	0.796
Cosyvoice	4.29	0.609	3.63	0.723
Cosyvoice2	2.57	0.652	1.45	0.748
GLM-4-Voice	2.91	-	2.10	-
Minmo	2.90	-	2.48	-
FLM-Audio (SFT-2)	2.95	0.543*	2.10	0.601*

4.3 Full-duplex Chatting

For LLM-based assistants, full-duplex chatting differs substantially from traditional text-based multi-modal instruction-following, particularly with respect to human preference. In instruction-following tasks, users often value detailed, elaborate responses, such as those required for programming or complex reasoning [17, 8]. In natural spoken conversations, however, users typically prefer concise, summarized, or even intentionally evasive replies.

To capture these differences, we conduct a comprehensive evaluation combining both automatic metrics and human judgment.

Automatic evaluation. We construct a speech instruction-following test set using publicly available Chinese prompts formatted in the style of AlpacaEval [22]. Prompts are converted into audio using our TTS pipeline. DeepSeek-V3 [25] is employed as a reference model to assign quality scores (0–10 scale) by comparing candidate textual responses to ground-truth answers.

Human evaluation. We run a double-blind, head-to-head comparison between FLM-Audio and Qwen2.5-Omni [39], a state-of-the-art streaming chatbot. Five human annotators rate multi-turn audio responses across four dimensions: (1) Helpfulness, standing for the informativeness and relevance of content; (2) Naturalness, for conversational tone and linguistic fluency; (3) Responsiveness,

representing reaction speed to interruptions and dynamic user input; and (4) Robustness, which means stability under noisy real-world conditions. This benchmark shares the same spirit as [24], but is constructed in Chinese.

Results. Table 6 summarizes the results. Compared with Qwen2.5-Omni, FLM-Audio delivers responses of comparable quality in terms of helpfulness, as confirmed by both automatic scoring and human ratings. More importantly, in dimensions that matter most for real-time interaction: naturalness, responsiveness, and robustness, FLM-Audio demonstrates a clear advantage. We attribute this to the model's native full-duplex design and the effectiveness of the dual training paradigm.

Ablation study. We further compare against a baseline trained without the semi-duplex *Fine-tuning-1* stage (i.e., omitting ASR-style supervision). This variant shows a marked drop in instruction-following ability, underscoring the importance of retaining the dual data format in SFT. In particular, the ASR-style organization significantly strengthens audio understanding, validating the design of our training pipeline.

Model	Instruct	Human Evaluation				
	LLM-score	Helpfulness	Naturalness	Responsiveness	Robustness	
Qwen-2.5-omni	6.36	7.4	7.9	8.1	7.7	
FLM-Audio w/o SFT-1	4.59	-	-	-	-	
FLM-Audio SFT full	6.58	7.2	8.2	8.8	8.0	

Table 6: Full-duplex Chatting results. Automatic and human evaluation results are included.

4.4 Answers to Research Questions

We now revisit the research questions posed at the beginning of Section 4:

RQ1: In native full-duplex systems, do natural monologues improve semantic understanding as hypothesized? Yes. As shown in Section 4.1, FLM-Audio matches Moshi's performance after only the Post-training-1 stage, despite being trained with less than 15% of Moshi's audio data. Since both models share the same RQ-Transformer backbone and rely on coarse third-party ASR transcripts at this stage, the performance advantage is best explained by our natural monologue design. Additional evidence comes from final instruct-following results: FLM-Audio reaches performance levels comparable to state-of-the-art systems such as Qwen-2.5-Omni, whereas Moshi has been reported to lag behind in this area [46]. These results also support our hypothesis that meaningful modifications in data organization, alignment strategies, and training paradigms can bring significant gains with the same LLM model architecture kept intact.

RQ2: How effective is the dual data-format strategy across training stages, and how crucial is it to final performance? The TTS-style format is essential for any responsive full-duplex system, including both FLM-Audio and Moshi. Thus, the key question is whether the additional ASR-style format provides a measurable benefit. Results in Table 4 and Table 6 confirm that it does: models trained without ASR-style supervision show clear disadvantages in audio understanding and instruction-following, underscoring the importance of dual-format training.

RQ3: How does FLM-Audio compare against state-of-the-art full-duplex chatbots in terms of responsiveness, speech quality, and dialog capability? As demonstrated in Section 4.3, FLM-Audio achieves comparable overall response quality to Qwen-2.5-Omni, while delivering superior naturalness, responsiveness, and robustness in interactive settings. These results affirm that native full-duplex design, coupled with our dual training paradigm, enhances both the quality and the real-time usability of spoken dialog systems.

5 Conclusion and Future Challenges

In this paper, we explored ways to advance native full-duplex audio chatbots. We introduced a novel alignment strategy, natural monologues, together with a training pipeline that integrates dual ASR-like and TTS-like capabilities. Building on this design, we developed and released FLM-Audio, a bilingual chatbot with native full duplexity. Compared with the most related baseline Moshi,

FLM-Audio achieves equivalent response latency while delivering substantially stronger language modeling and instruction-following performance. Our experimental results validate the effectiveness of natural monologues and support our central hypothesis that they benefit native full-duplex systems when combined with dual training.

Constrained by data volume and computational resources, we have not yet scaled FLM-Audio to larger parameter counts—a direction where native duplex models could exhibit even greater advantages over TDM-based approaches. We hope this research will inspire further exploration into scaling native full-duplex architectures, both to push the performance upper bound of task-solving and to provide a more comprehensive comparison against TDM-based solutions.

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