

# MMEDFD: A REAL-WORLD HEALTHCARE BENCHMARK FOR MULTI-TURN FULL-DUPLEX AUTOMATIC SPEECH RECOGNITION

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## ABSTRACT

Automatic speech recognition (ASR) in clinical dialogue demands robustness to full-duplex interaction, speaker overlap, and low-latency constraints, yet open benchmarks remain scarce. We present MMedFD, the first real-world Chinese healthcare ASR corpus designed for multi-turn, full-duplex settings. Captured from a deployed AI assistant, the dataset comprises 5,805 annotated sessions with synchronized user and mixed-channel views, RTTM/CTM timing, and role labels. We introduce a model-agnostic pipeline for streaming segmentation, speaker attribution, and dialogue memory, and fine-tune Whisper-small on role-concatenated audio for long-context recognition. ASR evaluation includes WER, CER, and HC-WER, which measures concept-level accuracy across healthcare settings. LLM-generated responses are assessed using rubric-based and pairwise protocols. MMedFD establishes a reproducible framework for benchmarking streaming ASR and end-to-end duplex agents in healthcare deployment. The dataset and related resources are publicly available at <https://github.com/Kinetics-JOJO/MMedFD>.

**Index Terms**— Automatic Speech Recognition, Healthcare Dialogue, Full-Duplex, Multi-Turn Dialogue

## 1. INTRODUCTION

Automatic speech recognition (ASR) converts speech into text streams and is increasingly important in clinical work [1]. High-quality transcripts improve documentation and support downstream tasks such as entity capture, concept linking, and note generation that benefit patient care and auditing [2, 3]. However, ASR continues to be challenged

by real-world healthcare dialogues involving multi-turn and highly dynamic content. These dialogues contain frequent interruptions and overlapping speech and demand reliable speaker attribution. Also, ASR systems must maintain dialogue memory, recover after barge-in, and keep latency low in streaming mode [4].

Recent full-duplex dialogue schemes coordinate listening and speaking via learned controllers, yielding significant latency reductions over half-duplex interaction. These results highlight the potential of integrating streaming ASR with overlap-aware control mechanisms in deployment [5]. However, open corpora and harmonized evaluation standards are still underdeveloped in Chinese clinical ASR. Public, real-world benchmarks are scarce. PriMock57 [6] offers simulated primary care consultations suitable for controlled experimentation, while also highlighting the lack of publicly available, real-world Chinese clinical ASR corpora with standardized divisions for rigorous and comparable evaluations.

Multi-turn spoken benchmarks increasingly adopt rubric-guided evaluation to assess model competence beyond literal word accuracy [7]. Real-world healthcare dialogue faces similar challenges, where plain word error rate (WER) is insufficient due to the need for metrics that capture medical concepts, dialogue coherence, and speaker-role consistency. Although postprocessing based on large language models (LLM-based) can reduce WER and improve recognition of medical concepts, its efficacy under multi-turn, full-duplex conditions remains unverified [1]. Recent surveys further reveal this research gap, motivating end-to-end architectures that jointly model recognition, speaker diarization, and dialogue management under operational constraints [3, 4].

Therefore, we proposed MMedFD, a real-world benchmark for multi-turn, full-duplex Chinese healthcare dialogue. Figure 1 provides a unified protocol for corpus construction

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and dialogue evaluation. Our main contributions are:

1. We released a real-world Chinese healthcare dialogue corpus with multi-turn structure and consented de-identification, annotated with role labels and medical entities for supervised training and evaluation.
2. We proposed a model-agnostic full-duplex pipeline that standardizes streaming segmentation, speaker diarization, context packaging, and cross-turn memory, enabling real-time barge-in and overlap handling.
3. We conducted a comprehensive evaluation strategy for ASR, considering healthcare precision, entity-level precision recall, and metrics for coherence of dialogue and consistency of roles.

## 2. METHODOLOGY

### 2.1. Data Acquisition

We collected speech from a full-duplex healthcare assistant during internal testing (beta version). The assistant continuously listened while generating synthesized replies. To reflect deployment acoustics, we preserved acoustic echo cancellation (AEC), automatic noise suppression (ANS), and automatic gain control (AGC) [8]. Each session was stored as 16 kHz 16-bit long-form single-channel pulse code modulation (PCM) with wall clock timestamps suitable for Rich Transcription Time Marked (RTTM) turn annotation and Conversation Time Marked (CTM) word alignment [9]. We archived a separate text-to-speech (TTS) waveform for each agent reply with a stable identifier and order, the LLM-generated text, role labels, and a session manifest linking text to audio. The audio agent generated two synchronized views without filtering. The conversation view retained the complete mixed timeline. The user view excluded non-user segments while preserving residual echo to reflect full-duplex artifacts.

### 2.2. Data Pre-processing

Pre-processing integrates dialogue filtering with signal conditioning. A LLM screens for personally identifiable information (PII), semantic validity, and healthcare relevance, following governance-first curation practices as in the BigScience ROOTS corpus [10]. Pre-processing combined dialogue filtering with signal conditioning. A LLM screened for personally identifiable information (PII), semantic validity, and healthcare relevance, following governance-first curation practices consistent with the BigScience ROOTS corpus [10]. PII-positive items were gated from annotator access and auto-waived. Remaining content was manually verified and redacted prior to release. Audio was conditioned through DC offset removal, peak limiting, root mean square (RMS) normalization, and band-limiting. Segmentation was performed

using Silero voice activity detection (VAD) [11] with padding and short-gap merging. Non-speech audio longer than one second was excluded from the user view and retained in the conversation view. Playback-aware diarization, based on pyannote-style modeling, refined user-agent boundaries and identified overlaps excluded from supervised training [12]. Residual echo was detected by correlating the microphone signal with the agent TTS reference and was masked or down-weighted [8]. This stage produced RTTM turns, user-only segmentation with per-segment signal-to-noise ratio (SNR), and updated session manifests.

### 2.3. Quality Control

The quality control module verified linguistic fidelity, privacy, role labeling, and split hygiene. A domain-adapted end-to-end ASR model transcribed the user view and forced alignment anchored word timings to the conversation waveform to produce CTM files consistent with RTTM [13, 9]. Annotators followed predefined rules. TTS leakage resulting from AEC failures was not considered user speech. Segments with acoustic ambiguity or ASR confidence below 0.90 were marked unclear. Text normalization accounted for numerals, dates, units, drug names, and abbreviations while maintaining alignment with audio. This preserved semantic-acoustic correspondence across modalities and improved data quality. De-identification replaced personal identifiers with placeholders. Dual validation was applied using human annotators and LLM. Session-level splits were enforced when both speakers spoke concurrently. Each release included raw conversation audio, user segments, RTTM and CTM files, normalized transcripts with placeholders, and a manifest of known artifacts.

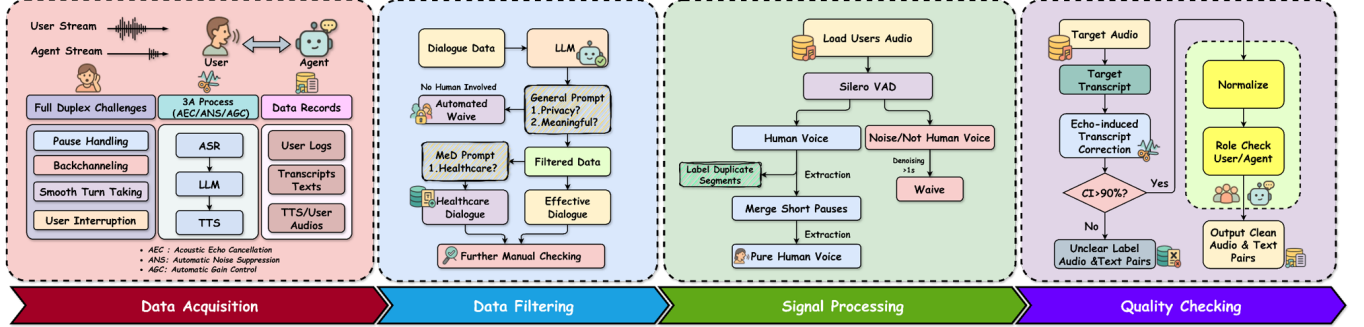
## 3. EXPERIMENTS

### 3.1. Experimental Setups

We fine-tuned Whisper-small [14] end-to-end on the Chinese training split for automatic speech recognition in healthcare dialogue. Role-concatenated audio streams were constructed by merging all user and agent turns separately, allowing long-context normalization and improved terminology coverage without requiring turn-level alignment. All models were trained monolingually on the Chinese portion of the corpus and evaluated on the held-out test split.

### 3.2. Implementation Details

We curated the corpus with a human and LLM-based screen to remove low-quality audio, unsafe content, and malformed transcripts, yielding 5,805 dialogues, 4,926 turns and 39.04 h. The dataset was split into 4,644 training and 1,161 held-out dialogues, preserving speaker and session disjointness. Text was preprocessed with standard normalization and consistent



**Fig. 1.** Overview of the four-stage pipeline from left to right, comprising Data Acquisition, Data Filtering, Signal Processing, and Quality Checking to produce clean, high quality audio and text pairs.

punctuation handling. Models were trained on  $4 \times$  NVIDIA L20 GPUs with batch size 8, learning rate  $1 \times 10^{-4}$  for 1,000 epochs.

### 3.3. Evaluation Protocol

We evaluated the test split of our Chinese healthcare benchmark comprising 1,161 dialogues. All systems used a shared text-normalization pipeline. The decoding hyperparameters for ASR and LLM generation were tuned on the development set and fixed during testing.

#### 3.3.1. ASR Evaluation Metrics

(i) Word/Character Error Rate (WER/CER). For reference  $y^*$  and hypothesis  $\hat{y}$ , with  $S$ ,  $D$ , and  $I$  representing the number of substitutions, deletions, and insertions (as defined by the Levenshtein distance), and  $N$  being the total number of tokens in the reference (words for WER, characters for CER).

$$\text{WER}(y^*, \hat{y}) = \frac{S+D+I}{N}, \quad \text{CER}(y^*, \hat{y}) = \frac{S_c+D_c+I_c}{N_c}. \quad (1)$$

(ii) Healthcare WER (HC-WER). Adapting the *Medical Concept WER (MC-WER)* idea, we compute Levenshtein distance over medical-concept sequences rather than over all tokens. Let the category set be  $\mathcal{C} = \{\text{Dis}, \text{Proc}, \text{Test}, \text{Med}\}$ , corresponding to *Diseases and Conditions*, *Procedures and Therapies*, *Tests and Diagnostics*, and *Medications and Drugs*. A category-specific extractor  $\pi_k(\cdot)$  maps text to the in-order sequence of canonical surface forms in category  $k \in \mathcal{C}$ . With  $E_k^* = \pi_k(y^*)$  and  $\hat{E}_k = \pi_k(\hat{y})$ , define the category error

$$\text{ER}_k(y^*, \hat{y}) = \frac{L(E_k^*, \hat{E}_k)}{\max(1, |E_k^*|)}, \quad (2)$$

where  $L(\cdot, \cdot)$  is the edit distance on concept sequences. The overall score is the average across categories,

$$\text{HC-WER}(y^*, \hat{y}) = \frac{1}{|\mathcal{C}|} \sum_{k \in \mathcal{C}} \text{ER}_k(y^*, \hat{y}). \quad (3)$$

Role-concatenated audio streams were processed per session and role for ASR, and standard recognition metrics were computed after normalization.

#### 3.3.2. Evaluations of Response Quality

Evaluations followed a cascaded setup where ASR transcripts were provided to text-only LLMs to generate agent responses. A fixed GPT-5 judge scored all outputs using consistent prompts and decoding parameters. ASR metrics were computed after shared normalization under fixed decoding. Confidence intervals were estimated using a conversation-level bootstrap. LLM reply quality was assessed separately using PairEval [15] and G-Eval [16]. PairEval applied pairwise comparison with penalties for repetition, off-topic content, role confusion, and contradictions, reporting Win, Tie, and Any-Failure. G-Eval used a reference-based rubric across five dimensions, including correctness, fulfillment, specificity or actionability, safety, and coherence, along with an overall score. Mean scores with 95% confidence intervals were reported.

## 4. RESULTS

### 4.1. Benchmark Description

MMedFD is a benchmark for Chinese healthcare spoken dialogue constructed from live user-agent interactions under full-duplex conditions. The corpus contains 136.9 hours of role-labeled, turn-segmented transcripts across 1,805 dialogs and 10,814 turns. As shown in Table 1, most existing healthcare corpora collected in real-world settings lack explicit multi-turn annotation and rarely include full-duplex recordings. To the best of our knowledge, this is the first Chinese healthcare benchmark collected in real-world settings and annotated at multi-turn granularity under full-duplex operation. It supports systematic evaluation of duplex dialogue systems and ASR models under realistic timing constraints, including interruption management and turn-taking behavior in healthcare scenarios.

**Table 1.** Comparison of spoken-dialogue benchmarks and their evaluation protocols, including healthcare setting, scale, and language.

Benchmark	Multi-Turn	Full-Duplex	Health-Care	Nature	Roles	Dur. (h)	#Dialogs	#Turns	Language	Evaluation
MultiMed[3]	×	×	✓	Real-world	6	150	—	—	Multiling.	ASR(WER/CER)
VietMed[17]	×	×	✓	Real-world	6	16	—	—	Vietnamese	ASR(WER)
PriMock57[6]	✓	×	✓	Simulated	2	9	57	≈5244	English	ASR(WER), Task
Fareez et al.[18]	✓	×	✓	Simulated	2	55.15	272	—	English	ASR(WER), Human-Eval
myMediCon[19]	×	×	✓	Read	2	11	—	—	Burmese	ASR(WER)
AfriSpeech-200[20]	×	×	✓	Mixed	1	≈123	—	—	Afr. English	ASR(WER)
SpokenWOZ[21]	✓	×	×	Real-world	2	249	5,700	203,000	English	ASR(WER), Task
VoxDialogue[22]	✓	×	×	Mixed	2	42.56	4,500	30,700	English	LLM-Eval
MTalk-Bench[7]	✓	×	×	Mixed	2	2.45	90	568	English	S2S, LLM-Eval, Human-Eval
MMedFD (ours)	✓	✓	✓	Real-world	2	136.91	1,805	10,814	Chinese	ASR(WER/MC-WER), LLM-Eval

**Notes:** The symbols ✓ and × denote presence and absence, respectively, “—” indicates information not reported. Definitions: *Multi-turn* indicates explicit turn structure with cross-turn context, *Full-duplex* refers to user-agent settings in which the system speaks while continuously listening, *Healthcare* marks corpora collected in clinical/medical contexts. *Nature* categorizes collection modality as *Real-world* (naturally occurring audio), *Simulated* (scripted/acted clinical dialogues), *Read* (read speech), or *Mixed* (combined sources). *Scale:* *Dur. (h)* denotes total hours, *#Dialogs* counts conversational sessions, *#Turns* counts utterance-level turns, *Roles* indicates the number of distinct speaker roles. *Evaluation* abbreviations: *ASR* (Automatic Speech Recognition), *WER* (Word Error Rate), *CER* (Character Error Rate), *MC-WER* (medical-content WER), *Task* (objective task metrics such as dialogue-state accuracy, slot F1, task success), *LLM-Eval* (Large Language Model-based evaluation), *Human-Eval* (human evaluation), *TTS* (Text-to-Speech evaluation), and *S2S* (Speech-to-Speech evaluation via arena/rubrics).

**Table 2.** Role-wise ASR metrics on the train and test splits

Role	Metrics: Mean%					
	WER		Hc-WER (95% CI)		CER	
	Train	Test	Train	Test	Train	Test
User	54.56	53.11	16.83 (15.51–18.16)	15.37 (12.97–17.77)	50.51	52.08
Agent	1.92	1.84	9.66 (9.17–10.15)	9.81 (9.22–10.39)	1.86	1.81
All	28.24	27.48	13.25 (12.34–14.16)	12.59 (11.10–14.08)	26.19	26.95

**Notes.** Values are percentage means; 95% CIs are in parentheses. *All* is the unweighted average of User and Agent for each metric and split. WER = Word Error Rate; Hc-WER = Healthcare-aware WER; CER = Character Error Rate.

## 4.2. Evaluation Results

Two evaluation studies were conducted following the protocol. The first assessed ASR performance using role-specific metrics, including WER, CER, and HC-WER for user and agent utterances. Results are shown in Table 2. The second study used transcriptions from a fixed ASR system as input to text-only LLMs under uniform prompting and decoding configurations. We evaluated GPT-5 [23], Claude 4.1 [24], Gemini 2.5 [25], and Qwen3 [26] based on response quality. GPT-5 [23] was the examiner for these responses. Results are presented in Table 3.

## 5. CONCLUSION

MMedFD offers a reproducible real-world benchmark for full-duplex Chinese healthcare dialogue, combining governance-compliant data, synchronized acoustic views, and grounded evaluation from the perspective of healthcare. It reveals persistent challenges in barge-in, overlap, and role attribution, supporting progress in streaming ASR and end-to-end dialogue agents.

**Table 3.** LLM-judged results for healthcare queries using PairEval and G-Eval with a consistent GPT-5 judge.

PairEval (Pairwise Judge)			
Model	Win % (95% CI)	Tie %	Any-Failure %
GPT-5[23]	51.8 (49.0–54.5)	96.3	94.4
Claude-Opus-4.1[24]	50.1 (47.3–52.8)	99.8	99.8
Gemini-2.5-Pro[25]	52.3 (49.5–55.0)	95.0	92.2
Qwen3-30B-A3B[26]	51.3 (48.6–54.1)	97.0	93.8
Ours	49.0 (46.2–51.7)	97.0	95.0

G-Eval (Reference-Based Rubric)			
Model	Overall (95% CI)	Correctness %	Safety %
GPT-5[23]	3.9 (3.7–4.1)	35.2	35.2
Claude-Opus-4.1[24]	4.1 (3.9–4.2)	38.4	38.4
Gemini-2.5-Pro[25]	4.0 (3.8–4.1)	36.4	36.4
Qwen3-30B-A3B[26]	4.1 (3.9–4.2)	37.7	37.7
Ours	4.0 (3.9–4.1)	36.9	36.9

**PairEval** compares two model outputs for each query using a fixed LLM judge; Win% treats a win as 1 and a tie as 0.5, Tie% is the share of ties, and Any-Failure% is the share of responses that show any failure (repetition, off-topic content, role confusion, or contradiction).

**G-Eval** scores each output against references on a 1–5 rubric; we report the mean and 95% confidence intervals for *Overall* (usefulness and coherence), *Correctness* (alignment with references and medical facts), and *Safety* (avoiding harmful or inappropriate advice).

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