CMDAR: A Chinese Multi-scene Dynamic Audio Reasoning Benchmark with Diverse Challenges

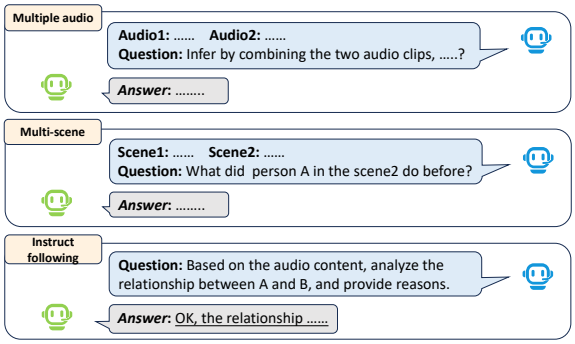
Anonymous ACL submission

Abstract

The ability to reason from audio, including speech, environmental sounds, and music, is essential for AI agents to interact effectively in real-world scenarios. Existing benchmarks mainly focus on *static* or *single-scene* settings and English audio data and do not fully capture scenarios where multiple speakers, unfolding events, and heterogeneous audio sources interact. To address these challenges, we introduce **CMDAR**, *a chinese benchmark for evaluating models on complex, multi-scene, and dynamically evolving audio reasoning tasks.* CMDAR comprises 3,000 carefully curated question–answer pairs linked to diverse audio clips, covering five categories of complex reasoning and spanning three question types. We benchmark 26 state-of-the-art audio language models on CMDAR and observe that they exhibit limitations in complex reasoning tasks. In CMDAR-main, Qwen2.5-Omni (open-source) achieves 76.67% accuracy, whereas GPT-4o Audio (closed-source) reaches 68.47%. However, GPT-4o Audio substantially outperforms Qwen2.5-Omni on the more challenging multiple-choice with multiple audios and open-ended tasks. And we provide *detail analysis corresponding suggestions for the future development of large audio language models (LALMs).* Code and benchmark can be found at https://anonymous.4open.science/r/CMDAR-C598.

1 Introduction

The ability to reason from audio, including speech, paralinguistic cues, environmental sounds, and music, is essential for AI agents to interact effectively in real-world scenarios. Real-world environments are rich in overlapping auditory signals that convey linguistic content, social cues, temporal patterns, and environmental context (Wei et al., 2022; Nam, 2025). Effective reasoning over these audio streams is critical for AI agents to understand dynamic interactions, anticipate unfolding events, and support decision-making in applications such as autonomous navigation, audio event monitoring, and embodied household agents (Chen et al., 2020; Gao et al., 2023; Yeow et al., 2024).



	Mixed audio	Multiple audio	Open Ended	Multi-scene within One audio	Chinese	Instruct following
AudioBench	×	×	√	×	×	×
AIR-Bench	×	×	√	×	×	×
MMAU	×	×	×	×	×	×
MMAU-pro	√	√	√	×	×	√
MMAR	√	×	×	×	×	×
CMDAR(Ours)	√	√	√	√	√	√

Figure 1: **The differences between the existing benchmark and CMDAR.** Tasks in CMDAR are essential skills for AI Agent.

So far, various benchmarks have been proposed. AudioBench (Wang et al., 2025a) and AIR-Bench (Yang et al., 2024) are benchmark designed for large audio language models, aiming to comprehensively evaluate the understanding and reasoning ability of these models on audio content, but only focusing on shallow reasoning ability. MMAU (Sakshi et al., 2025) and MMAR focus more on the evaluation of deep reasoning ability of audio, but they pay more attention to perception samples, including counting and classification perception tasks, mainly for single scene and single audio problems, and do not include the evaluation of open-ended tasks, resulting in insufficient evaluation. Recently, MMAU-pro (Kumar et al., 2025) addressed the evaluation problem of multi-audio, but all the above evaluations only focus on English data, and do not focus on the investigation of

Chinese audio reasoning ability and instruction following ability. To address the limitations of current audio reasoning benchmarks, we propose CMDAR, a Chinese comprehensive test benchmark aimed at evaluating the complex logical reasoning ability of LALMs in dynamic scenarios. CMDAR has 3000 high-quality questions from real scenarios, with multiple types of reasoning tasks (including continuous scenarios, causal scenarios, and multi scenario tasks) and comprehensive question types. All questions and reference answers are strictly reviewed by experts. The differences between the existing benchmark and CMDAR are summarized in Figure 1. In addition, we also propose a high-quality data construction process and a comprehensive and effective evaluation method.

We benchmark 26 state-of-the-art audio language models on CMDAR and observe that they exhibit limitations in complex reasoning tasks. In the CMDAR-main, Qwen2.5-Omni (open-source) achieves 76.67% accuracy, whereas GPT-4o Audio (closed-source) reaches 68.47%. Among different tasks of single-choice questions, Qwen2.5-Omni (Xu et al., 2025a) performs worst on temporal reasoning (71.43%), while GPT-4o Audio struggles most on scene reasoning (61.27%). However, GPT-4o Audio substantially outperforms Qwen2.5-Omni on the more challenging multiple-choice with multiple audios and open-ended tasks. Across all three question types, no model surpasses 80% performance. These results indicate that even the most powerful models currently still have significant room for improvement, and finally we provide corresponding suggestions for the future development of LALMs. These findings underscore the unique challenges posed by CMDAR and its value as a benchmark for advancing audio reasoning research. Overall, our contributions are three-fold:

1. We introduce CMDAR, a first large-scale Chinese benchmark focusing on evaluating multi-scene and dynamic audio reasoning across five categories, spanning three question types.
2. We construct a high-quality data construction workflow and provide curated audio clips paired with human re-annotated questions and answers to systematically evaluate both perceptual and high-level reasoning abilities.
3. We conduct a comprehensive evaluation of state-of-the-art models, revealing the significant challenges posed by CMDAR and give suggestions of highlighting key areas for improvement in next-generation audio reasoning agents.

2 Related Work

2.1 Audio-Language Models

Recent advances in large language models (LLMs) and cross-modal learning have driven substantial progress in audio-language research. Typical approaches jointly leverage speech, music, and general audio data, followed by instruction tuning to endow models with comprehension and instruction-following abilities. Open-source systems such as Qwen-Audio-Chat (Chu et al., 2023), Qwen2-Audio-Instruct (Chu et al., 2024), Audio Flamingo (Ghosh et al., 2025; Goel et al., 2025), SALMONN (Tang et al., 2024), and DeSTA2.5-Audio (Lu et al., 2025) report competitive results. More recent efforts, including Audio-CoT (Ma et al., 2025a), Audio-Reasoner (Xie et al., 2025), and R1-AQA (Li et al., 2025), focus on multi-step reasoning and challenging audio QA. Among proprietary systems, GPT-4o-Audio achieves the highest overall performance, while other commercial models such as Kimi-Audio (KimiTeam et al., 2025) and MiDashengLM (Dinkel et al., 2025) are also evaluated. Fully multimodal models such as Omni-R1 (Zhong et al., 2025) and Qwen2.5-Omni (Xu et al., 2025a) advance audio-text reasoning. We also benchmark cascaded audio-language models for a holistic comparison.

2.2 Audio Understanding and Reasoning Benchmarks

Prior works have explored audio question answering and compositional reasoning across speech, music, and environmental sounds. Early efforts include Lipping et al. (2022), a crowdsourced dataset with yes/no and single-word answers, and Ghosh et al. (2024b), which targets order- and attribute-level compositional reasoning with composition-aware fine-tuning for CLAP (Wu et al., 2023). In music, Melechovský et al. (2024) provides a controllable text-to-music system with theory-informed captions, and Weck et al. (2024) offers a human-validated multiple-choice benchmark probing music knowledge. For speech, Zhao et al. (2024) curates large-scale spoken QA in free-form and multiple-choice formats, while Huang et al. (2023) establishes a collaborative instruction-tuning benchmark across diverse speech tasks.

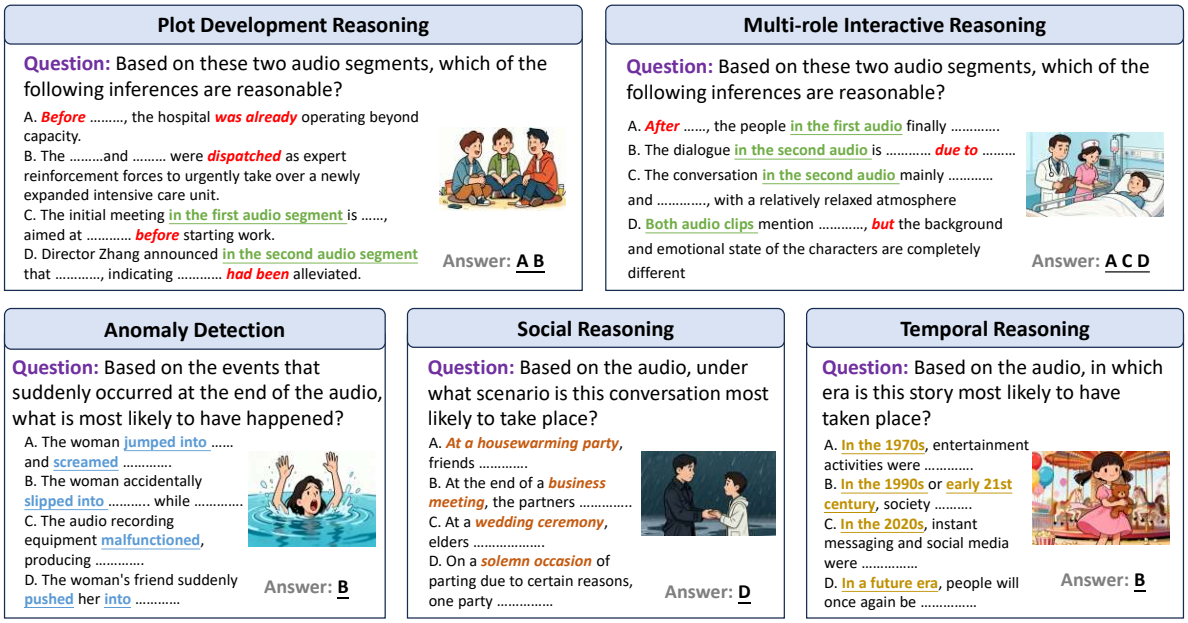


Figure 2: **Examples** from CMDAR showcase the diversity of complex dynamic reasoning tasks and also reveal the design of our newly proposed multiple-choice questions. These tasks not only demonstrate the depth of CMDAR in multidimensional capability assessment but also reflect its high standards of challenge.

Broader evaluations include Wang et al. (2025a), covering speech, scenes, and paralinguistics under instruction following, and Yang et al. (2024), which assesses generative comprehension and chat-based interaction over speech, sounds, and music. More recent reasoning-focused suites such as Sakshi et al. (2025), Ma et al. (2025b), and Wang et al. (2025b) emphasize multi-step perception and domain knowledge, revealing persistent gaps in multimodal integration and deep audio reasoning.

3 CMDAR benchmark

3.1 Overview of Benchmark

CMDAR is a benchmark test specifically designed to evaluate the reasoning capabilities of audio-language models in complex and dynamic scenarios. It encompasses 3,000 questions involving high-quality complex reasoning tasks of various types. Figure 2 illustrates examples of different categories and types of questions within this benchmark test. Each example consists of a meticulously designed question and a reference answer. The questions are semi-automatically generated by LLMs and manually annotated by experts and have undergone multiple rounds of screening to ensure their high quality. This benchmark test poses extremely high demands on the complex dynamic reasoning abilities of models, presenting a significant challenge.

CMDAR-main consists of 1,500 carefully designed single-choice questions for precise reasoning on complex audio, organized into five categories: scene understanding, social relationships and social reasoning, event reasoning, temporal reasoning, and anomaly detection and safety. Detailed descriptions and evaluation focuses for each category are provided in the Appendix A.

CMDAR-open anchors its question bank in real-world events and scenarios. The traditional closed-set multiple-choice evaluation method can no longer adequately reflect the core capabilities required by AI agents in open real-world environments. The uncertainty inherent in open-ended questions poses greater challenge to the agents' authentic response and judgment abilities. Task categories are the same as CMDAR-main.

CMDAR-multi is the benchmark to incorporate multi-audio, multiple-choice questions. By embedding real-world events and semantic ambiguities into options, it challenges models to make interpretable decisions even under mishearing, omission, or bias. Detailed descriptions and evaluation focuses for each category are provided in the Appendix A.

Question Distribution and Difficulty. Figure 5 shows the distribution of questions across different categories and subcategories and summarizes the key statistics of CMDAR. The average lengths of questions and answers are 30.68 words and 18.69 words. The average length of the audio clips is

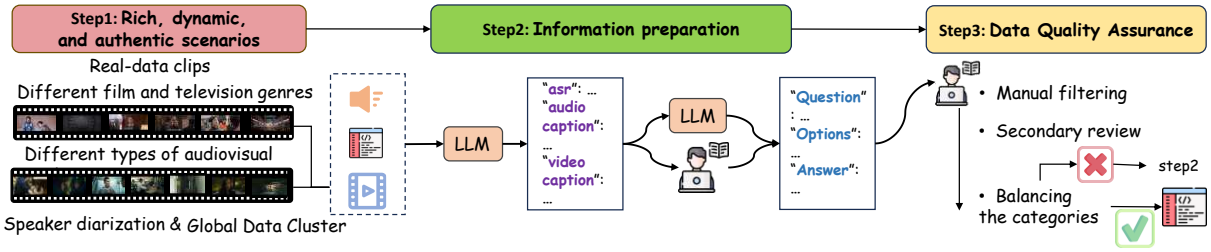


Figure 3: **Data Construction Pipeline**: It consists of three parts: Data Preparation, Audio Pipeline, and Data Quality Assurance, to ensure high quality and consistency of the data.

25.11 seconds,longer than the previous benchmark MMAU which is about 10 seconds and MMAR, which is about 19.94 seconds. Moreover, the three types of questions in CMDAR go beyond only the single-choice question type in MMAU and MMAR, offering a more complex and comprehensive measure of audio reasoning capabilities.

3.2 Data construction pipeline

As illustrated in Figure 3, we propose a high-quality data-construction workflow, which is divided into three main steps. The details of prompts are provided in the Appendix D.

Data Preparation. CMDAR uses Chinese films as metadata source, covering various genres and themes (Details are provided in Appendix B). Leveraging multi-narrative and high-production-value films to construct complex and dynamic scenes, we randomly extracted 20-40 seconds clips from the target films to accommodate the existing limitations of audio input, while ensuring the clip length is sufficient to contain events and complex information. Then we use PyAnnote toolkit[1] to segment the clips and perform global clustering of audio clips with the same speaker to form the audio pairs required for multiple-choice questions.

Audio Pipeline. Based on the above corpus, we design a three-step pipeline: ***i)* Information Preparation.** We apply FunASR[2] for speech recognition and use Gemini-2.5-pro and Qwen2.5-VL to generate multimodal descriptions, laying the foundation for question construction. ***ii)* Framework Construction.** Domain experts are invited to design question types and categories, and to select complex, dynamic scenarios that sufficiently challenge LALMs. ***iii)* Content and Distractor Option Generation.** We use Gemini-2.5-pro to automatically generate question-answer pairs and distractor options. For multi-audio Q&A, we focus on combining independent audio segments with shared contextual information, while distractor options for multiple-choice questions were evenly distributed among the information from independent audio segments and shared audio segments.

Data Quality Assurance. We implement multiple traceable steps to ensure high-quality data: ***i)* Expert Annotation Filtering.** Experts refine and annotate the Q&A pairs, generating complete metadata including identifiers, timestamps, questions, and answers. We use strict standards to manually screen for invalid, low-quality, harmful, or irrelevant samples, ensuring that all issues revolve around the audio content. More screening criteria are provided in the Appendix E. ***ii)* Secondary Review.** Conducting a second screening according to data screening standards to ensure no omissions and no systematic biases. ***iii)* Category Balancing.** Ensuring a balanced distribution of question categories to improve the quality of the test benchmark. If not, returning to Step2 until balance is achieved.

3.3 Evaluation metrics

In this section, we introduce the evaluation methods for CMDAR. In order to maintain fairness and consistency, we adopt different evaluation methods for different question types.

CMDAR-main. We use accuracy as the evaluation metric. Since LALMs tend to response option content, we adopt the same response processing pipeline as MMAU, using robust regular expressions to match the answer strings with the given options and calculate the accuracy. For each sample, $acc = 1$ if $string_match(response, answer) = True$, otherwise, $acc = 0$.

CMDAR-open. We employ a state-of-the-art LLM as an automated evaluator. The evaluator rates the model's answer on a scale of 0 to 10 based on the given scoring prompt. These prompts consider the usefulness, relevance, accuracy, and comprehensiveness of the answer. Detailed prompt design and examples are provided in the Appendix C.

[1] https://github.com/pyannote/pyannote-audio
[2] https://github.com/modelscope/FunASR

Model	Size	Type	SR	ER	SU	AD	TR	Avg(%)
Random guess	-	-	24.40	26.06	25.04	26.38	25.41	24.78
Human	-	-	92.64	89.24	92.13	90.69	93.14	92.66
Non-cascaded Model								
Qwen2-Audio-Instruct (Chu et al., 2024) ‡ ⋇	7B	LALMs	38.07	31.13	23.12	35.06	27.14	33.60
Qwen-Audio-Chat (Chu et al., 2023) ⋇	8.4B	LALMs	17.93	20.34	10.98	15.52	22.86	17.73
Audio Flamingo 2 (Ghosh et al., 2025)	3B	LALMs	26.37	22.54	34.29	29.41	31.61	27.73
Audio Flamingo 3 (Goel et al., 2025)	7B	LALMs	24.00	24.28	21.43	20.83	16.67	22.20
Audio Flamingo 3 Chat	7B	LALMs	15.26	16.18	12.86	13.73	20.69	15.47
Kimi-Audio-Instruct (KimiTeam et al., 2025) ⋇	7B	LALMs	14.52	18.38	13.29	20.69	25.71	16.67
Omni-R1 (Zhong et al., 2025) ‡ ⋇	7B	OLMs	44.89	45.83	45.66	60.34	38.57	46.73
R1-AQA (Li et al., 2025) ‡ ⋇	7B	LALMs	39.11	41.18	27.17	35.06	38.57	37.80
SALAMONN (Tang et al., 2024) ⋇	7B	LALMs	36.45	29.76	37.55	35.29	37.89	34.75
Audio-Reasoner (Xie et al., 2025) ‡ ⋇	8.4B	LALMs	45.93	42.65	43.35	37.36	47.14	43.80
DeSTA2.5-Audio (Lu et al., 2025)	8B	LALMs	63.41	62.01	54.91	53.45	64.29	60.93
MiDashengLM (Dinkel et al., 2025) ‡ ⋇	7B	LALMs	68.44	65.69	62.43	**74.71**	70.00	67.80
GPT-4o mini Audio	-	LALMs	61.19	54.34	62.86	66.67	56.90	61.47
GPT-4o Audio	-	LALMs	68.15	73.53	61.27	63.22	**72.86**	68.47
Qwen2.5-Omni (Xu et al., 2025a) ⋇ †	3B	OLMs	63.26	66.67	63.58	58.62	61.43	63.60
Qwen2.5-Omni (Xu et al., 2025a) ⋇ †	7B	OLMs	**78.67**	**75.98**	**75.72**	73.56	71.43	**76.67**
Cascaded Model								
GPT-4o Audio + Qwen2.5-Omni	7B	-	56.59	53.68	50.87	55.75	54.29	54.93
GPT-4o Audio + Qwen2-Audio-Instruct	7B	LALMs	33.19	24.51	21.39	28.74	37.14	29.13
GPT-4o Audio + Llama-3-Ins.	8B	LLMs	55.70	48.77	46.82	60.92	58.57	53.53
GPT-4o Audio + DeepSeek-V3	-	LLMs	**82.52**	**76.88**	**87.14**	**82.84**	**82.18**	**82.13**
GPT-4o Audio + DeepSeek-R1	-	LLMs	46.52	39.31	34.29	41.42	43.10	43.33
Qwen2-Audio-Instruct + Llama-3-Instruct	8B	LLMs	54.62	45.41	54.74	54.43	57.98	53.93
Qwen2-Audio-Instruct + GPT-4o Audio	-	LALMs	59.41	49.71	68.57	60.29	65.52	59.67
Qwen2-Audio-Instruct + DeepSeek-R1	-	LLMs	42.52	39.95	30.64	37.36	34.29	39.47
Qwen2-Audio-Instruct + Qwen2.5-Omni	7B	-	49.04	46.57	40.46	48.28	45.71	47.13
Qwen2-Audio-Instruct + DeepSeek-V3	-	LLMs	76.44	74.29	76.44	77.01	67.63	74.80

Table 1: Results on the CMDAR-main benchmark for both audio language models and cascaded models are presented for five task categories, coving SR (Social Relationships and Social Reasoning), ER (Event Reasoning), SU (Scene Understanding), AD (Anomaly Detection and Safety), and TR (Temporal Reasoning). The best results are highlighted in **bold** and the second-best is underlined. ⋇ indicates that the model is trained on Chinese corpora. ‡ indicates that the model has undergone the RL(Reinforcement Learning) phase. † indicates that the model is available in different parameter size.

We reduce the randomness of the scoring by conducting multiple evaluations and swapping the positions of the answers.

CMDAR-multi. We use the following four metrics to measure model performance inspired by SATA-BENCH (Xu et al., 2025b), ***i)*** **Exact Match (EM)**: For each sample, if the model's predicted answer is as same as the correct answer, the accuracy is counted as 1; otherwise, it is counted as 0. The final EM is calculated as the average accuracy.

$$EM = \frac{1}{N}\sum_{i=1}^{N} 1\,(if\ P_i = T_i) \tag{1}$$

ii) **Jaccard Index (JI)**: For each sample, we calculate the intersection of the predicted and true answers divided by their union, and then take the average of all samples to measure the degree of overlap.

$$JI = \frac{1}{N}\sum_{i=1}^{N} \frac{|P_i \bigcap T_i|}{|P_i \bigcup T_i|} \tag{2}$$

iii) **Mean Average Precision (Precision)**: For each sample, we calculate the proportion of correctly predicted answers out of all predicted answers, and then take the average of all samples.

$$Precision = \frac{1}{N}\sum_{i=1}^{N} \frac{|P_i \bigcap T_i|}{|P_i|} \tag{3}$$

Model	Size	Type	SR	ER	SU	AD	TR	Avg
Qwen2-Audio-Instruct	7B	LALMs	6.70	6.56	5.89	6.81	**6.53**	6.58
Qwen-Audio-Chat	8.4B	LALMs	3.24	3.77	4.30	2.44	5.50	3.58
Audio Flamingo 2	3B	LALMs	1.57	1.87	2.32	2.37	1.00	1.78
Audio Flamingo 3	7B	LALMs	3.19	3.36	3.84	4.44	3.50	3.33
Audio Flamingo 3 Chat	7B	LALMs	1.58	1.81	1.91	2.82	1.00	1.73
Qwen2.5-Omni	3B	OLMs	3.76	3.85	4.27	2.90	2.00	3.82
Qwen2.5-Omni	7B	OLMs	4.53	4.62	4.79	3.81	2.56	4.58
GPT-4o Audio	-	LALMs	**7.62**	**7.34**	**7.60**	**7.42**	5.50	**7.46**
GPT-4o mini Audio	-	LALMs	5.57	5.14	4.64	6.53	5.50	5.30
DeSTA2.5-Audio	8B	LALMs	3.67	3.61	3.89	3.99	1.50	3.65
Kimi-Audio-Instruct	7B	LALMs	3.98	3.56	3.92	3.06	4.00	3.75
MiDashengLM	7B	LALMs	3.84	3.64	4.15	3.52	4.00	3.75
Omni-R1	7B	OLMs	1.56	1.73	1.69	2.39	1.00	1.66
R1-AQA	7B	LALMs	4.36	4.30	4.82	5.26	3.50	4.36
SALAMONN	7B	LALMs	2.34	2.47	2.49	2.81	2.50	2.41
Audio-Reasoner	8.4B	LALMs	3.23	3.41	3.65	2.16	2.06	3.34

Table 2: Scores of audio language models on the CMDAR-open benchmark are presented for each category. The best results are highlighted in **bold** and the second-best is underlined. The five categories are represented in the same way as in Table 1.

iv) **Mean Average Recall (Recall)**: For each sample, we calculate the proportion of correctly predicted answers out of all true answers, and then take the average of all samples.

$$Recall = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_i \bigcap T_i|}{|T_i|} \tag{4}$$

N is the total number of samples. P_i is the set of predicted labels for the i-th sample. T_i is the set of ground truth labels for the i-th sample.

4 Experiments

4.1 Setting

We evaluate the performance of both cascaded and non-cascaded models on CMDAR. The non-cascaded models include large audio-language models, large audio-reasoning models, and full-modal language models. The large audio-language models consist of Qwen-Audio-Chat (Chu et al., 2023), Qwen2-Audio-Instruct (Chu et al., 2024), SALAMONN (Tang et al., 2024), Audio Flamingo 2 (Ghosh et al., 2025), Audio Flamingo 3 Chat (Goel et al., 2025), MiDashengLM (Dinkel et al., 2025), etc. The large audio-reasoning models include Audio-Reasoner (Xie et al., 2025), etc. The full-modal language models include Omni-R1 (Zhong et al., 2025), Qwen2.5-Omni (Xu et al., 2025a), etc. The cascaded models based on captions include GPT-4o Audio + Qwen2-Audio-Instruct, Qwen2-Audio-Instruct + Llama-3-Instruct, etc. Considering the scarcity of Chinese audio reasoning data, some models lack of ability of Chinese reasoning or support for Chinese audio understanding. We annotate in the Table 1 whether they were trained using Chinese corpus to ensure fairness in evaluation. Please note that as our benchmark tests are automatically synthesized by Gemini, the results of Gemini related models will not be included. For the selection of models and detailed information, refer to the Appendix F.

4.2 Results

In this section, we preliminarily demonstrate the performance of various models in CMDAR, which is shown in Tables 1, 2 and 4.

Our Benchmark is Challenging. We incorporate the results of human evaluation and observe that the best model Qwen2.5-Omni-7B in CMDAR-main only achieve an accuracy of 76.67%. The highest score in CMDAR-open is only 7.46, which open-source model is also only 6.58. In CMDAR-multi, the scores of most models are very low, even less than 10%, indicating that CMDAR is difficult and challenging. In addition, the performance differences between different models are also significant, indicating that CMDAR has good discriminative ability.

To ensure the correctness and rationality of using LLM for open scoring, we randomly select 10% of samples and manually score the answers of the Qwen2-Audio-Instruct-7B, Qwen2.5-Omni-7B, and GPT-4o Audio. The manual scoring range is 0-5 points, with 5 points indicating complete cor-

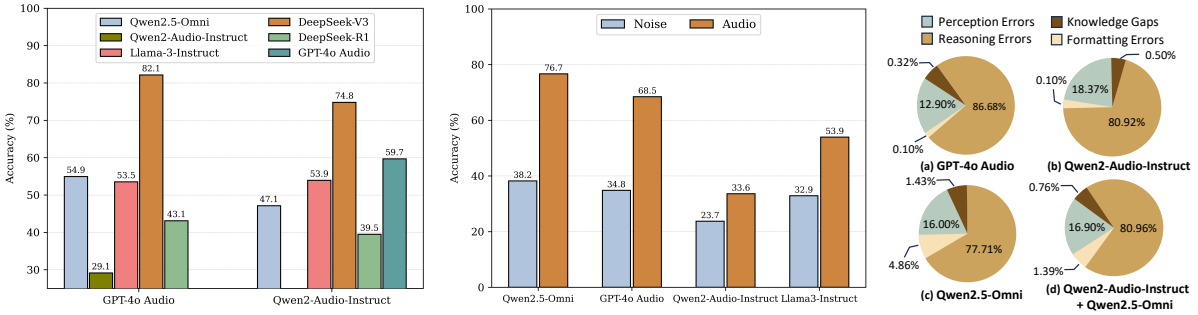


Figure 4: **Left:** Comparison of different combinations with the same caption model or the same reasoning model in the cascaded models. **Middle:** When Gaussian noise is used to replace the audio on CMDAR-main to test four models, the performance of all models experience a significant drop. **Right:** Distribution of error types

	Sample	**Qwen2-Audio-Instruct**	**Qwen2.5-Omni**	**GPT4o-Audio**
Pearson	50	0.95312	0.9268	0.9714
	Sample	**Qwen2-Audio-Instruct v.s. Qwen2.5-Omni**	**Qwen2.5-Omni v.s. GPT4o-Audio**	**GPT4o-Audio v.s. Qwen2-Audio-Instruct**
t-test	500	T: 6.421, P: 0.000	T: -11.866, P: 0.000	T: -8.389, P: 0.000

Table 3: Pearson correlation coefficient and t-test results of the correlation between LLM and human ratings.

rectness and clear expression. We calculate Pearson correlation coefficients, and all three coefficients are greater than 0.9, indicating that our human evaluation is highly correlated and reliable with LLM evaluation. Meanwhile, we conduct paired sample t-tests on these three models based on CMDAR-open, and all p-values are less than 0.05, indicating significant differences in evaluation scores among different models. Table 3 present these two results.

The Gap Between Open-Source and Closed-Source Models Remains Significant. we observe that most open-source models still have significant differences compared to the closed-source model GPT-4o Audio in CMDAR-main. This phenomenon is more pronounced in CMDAR-open and CMDAR-multi. The score of GPT-4o Audio in CMDAR-open is 13.37% higher than the best open-source model, and its indicators in CMDAR-multi are 92.78% higher than the best open-source model. These indicates that open-source models still have significant limitations in exploring perception and reasoning abilities.

4.3 Discussion

In order to explore deeper limitations and identify the abilities shortcomings, and potential improvement directions of LALMs, we design three experiments for further analysis. Finally, we propose suggestions for the future development of LALMs.

Analysis of Perception and Reasoning Capabilities of Cascaded caption Models. As shown in Figure 4, GPT-4o Audio (best closed-source model) and Qwen2-Audio-Instruct (baseline open-source model) are used as caption models, combined with other reasoning models for CMDAR-main. It can observe that ***i)*** Under the same caption, the combination of GPT-4o Audio and other models performs worse than using GPT-4o Audio alone, indicating that GPT-4o Audio has strong perceptual ability. ***ii)*** The combination of Qwen2-Audio-Instruct and other models is superior to using Qwen2-Audio-Instruct alone, indicating that the perceptual ability of Qwen2-Audio-Instruct is weaker. ***iii)*** When DeepSeek-V3 is used as a reasoning model, its results outperform those combined the same caption model with other reasoning models, and can be comparable to the best non-cascaded models, demonstrating its significant reasoning potential.

Gaussian Noise Replacement Experiment: Taking four different types of models as representatives, we replace the audio with Gaussian white noise of the same length and input it into the audio-language models. As shown in the middle of Figure 4, the accuracy of the models dropped significantly when they received white noise, approaching random guessing. This indicates that the models received audio information. However, the results also show that even with noisy audio, the models were still able to derive some answers from the textual questions.

Error Analysis: We classify incorrect answers of four models using Gemini-2.5-flash and find that

Model	Size	Type	EM(%) ↑	JI(%) ↑	Precision(%) ↑	Recall(%) ↑
Human	-	-	87.6	91.52	86.44	94.12
Qwen2-Audio-Instruct	7B	LALMs	4.00	22.48	28.22	16.67
Qwen-Audio-Chat	8.4B	LALMs	6.17	42.77	56.67	54.02
Qwen2.5-Omni	3B	OLMs	25.67	57.98	62.80	52.87
Qwen2.5-Omni	7B	OLMs	26.88	57.97	61.85	50.00
GPT-4o Audio	-	LALMs	**51.82**	**78.65**	**77.26**	**83.91**
GPT-4o mini Audio	-	LALMs	21.45	53.23	72.97	55.41
DeSTA2.5-Audio	8B	LALMs	15.38	55.47	47.05	51.13
Kimi-Audio-Instruct	7B	LALMs	15.74	69.97	53.47	53.45
MiDashengLM	7B	LALMs	8.72	51.60	52.60	48.96
Omni-R1	7B	OLMs	3.63	51.17	62.50	63.85
R1-AQA	7B	LALMs	2.42	18.58	18.77	18.07

Table 4: Results of audio language models on the CMDAR-multi benchmark are presented. Detailed results for each category can be found in the Appendix G. The best results are highlighted in **bold** and the second-best is underlined. The explanations for the four metrics are provided in 3.3.

reasoning errors were the main source of error for most models. For example, the rate of reasoning errors of GPT-4o Audio was 86.68%, while the other three types of errors were relatively low.

For LALMs, there are various reasons that lead to model errors. Firstly, LALMs tend to answer the content of options rather than just A/B/C/D like text reasoning models, which results in different models having *different preferences* in answering questions. For example, Omni-R1 often adds line breaks, and some models cannot fully restate the options. Secondly, LALMs generally have *randomness and instability*, and different prompts and runs can also lead to significant differences in accuracy. Detailed analysis and case studies are provided in Appendix H and Appendix I. Finally, *hallucination problem* that LALMs encounter mainly manifests as the creation of non-existent sound events or options. Most of the problems stem from the insufficient granularity of model perception, leading to the omission of key content.

Suggestions to guide the development of LALMs. We first emphasize that in the future training of LALMs, special attention should be paid to improving ⋇ **Chinese language proficiency**[3]. We suggest *adding more Chinese reasoning data to the training corpus* to enhance the model's understanding and reasoning ability in Chinese context. Secondly, by categorizing models by whether or not they underwent an ‡ **RL phase**, we found that in CMDAR, while it can bring positive improvements, *the improvement of RL is limited by the current LALMs foundations.* Furthermore, we compare † **the training phase and parameter size** of the models. Under the same architecture, the 7B model outperform the 3B model, but still has the second-largest perceptual error ratio. To address this issue, we should *focus more on data quality (such as fine-grained processing)* and a better post-training workflow, rather than continuing to increase the number of parameters. In the cascade experiment, we find a significant improvement in the accuracy of the reasoning model using DeepSeek-V3. When training LALMs without losing perceptual ability, we should *focus on data diversity (to alleviate the instability shown in experiments) and text specific abilities*. We believe that code or mathematical data can help improve audio reasoning ability.

[3]When some model is trained based on foundation model, Chinese ability should be the same as foundation model.

5 Conclusion

We introduce CMDAR, a Chinese benchmark for evaluating models on challenging, multi-scene, dynamically evolving audio reasoning tasks. CMDAR comprises 3,000 carefully curated question–answer pairs linked to diverse audio clips, covering five categories of complex reasoning across three question types. We evaluated 26 audio models, revealing that CMDAR poses substantial challenges across question formats and evaluation methods. Furthermore, we analyze gaps between open-source and closed-source models, and overall limitations in model audio understanding. Furthermore, we analyze the gap between open-source and closed-source models, the perceptual and reasoning capabilities of cascading caption models, and limitations of model audio reasoning, providing suggestions for future development.

Limitations

Our benchmark may has the following limitations.

Data. Our benchmark is based on monolingual Chinese data, which may have limitations due to language diversity. We hope that the audio community will focus on the development of Chinese audio reasoning capabilities.

Models. We have only tested a subset of LALMs. For the latest models, we will update the code leaderboard in a timely manner.

Evaluation. Although we conducted numerous experiments to validate the rationale for using LLM for assessment, it is undeniable that updates to the LLM framework can impact experimental results. We will update the leaderboard promptly and consider incorporating more robust metrics for a comprehensive evaluation of reasoning ability.

Analysis. Our analysis of the limitations and future development of LALMs is based on results from CMDAR and related work.

Ethics Statement

This study follows the relevant ethical guidelines of the institution and country, has obtained informed consent from all participants, and strictly protects their privacy and data security. The manual annotations in this work are solely for evaluation purposes in the 'Human–Large Language Model Protocol' research, and the generated annotations will not be included in the published resources. All manual evaluations are conducted by expert reviewers selected from the research team according to a predefined assessment plan. No personal data have been collected. The research process has no conflicts of interest, and the results are accurate and reliable. Therefore, we believe this work does not raise significant ethical concerns.

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A Task

A.1 Task Introduction

We divide the benchmark tests into five major task categories based on the idea of enhancing the complex dynamic audio capabilities and real mixed-scene reasoning capabilities of audio-language models. Below are detailed introductions to each category and the focus of the benchmark assessments.

Scene Understanding focuses on the holistic perception and semantic interpretation of complex, dynamic, multimodal scenarios. It is divided into three subtasks: Scene Localization, Scene Change Reasoning, and Scene Element Recognition. This category tests the models' ability to extract key entities, attributes, and states from multimodal information sources such as text and audio. It also evaluates their capacity to distinguish between common-sense and counter-common-sense elements in open-world scenarios, as well as to understand spatial layouts, functional relationships between objects, and causal constraints.

Social Relationships and Social Reasoning centers on modeling implicit social relationships, role identities, emotional motivations, and normative constraints between individuals. It consists of two subtasks: Social Intent Reasoning and Character Identity Association. This category assesses the models' ability to infer intimacy, power distance, and trust levels from dialogues, micro-expressions, gestures, and historical interactions. It also examines their capability to reason about the facade and subtext in multi-party interactions—such as irony, politeness, and implicit requests.

Event Reasoning emphasizes modeling and counterfactual thinking about the causal, conditional, and intervention effects of multi-step event chains. It is divided into two subtasks: Event Causal Reasoning and Event Sequence Reasoning. This category tests the models' ability to handle causal graphs with multiple causes for one effect and one cause for multiple effects.

Temporal Reasoning focuses on precisely modeling explicit and implicit temporal information, temporal constraints, and cross-scale dynamic evolution. It evaluates the models' ability to provide accurate answers to vague temporal questions and to infer the temporal priority relationships between events.

Anomaly Detection and Safety centers on rapidly identifying audio that deviates from the norm or implies risks in an open environment and proposing interpretable safety intervention strategies. This category tests the models' ability to locate subtle anomalies in multimodal inputs and to generate corresponding emergency response plans.

Plot Development Reasoning focuses on the ability to model the coherence of narrative logic, the evolution path of conflicts, and the possibility of outcomes. It tests the model's ability to infer reasonable directions for subsequent plot development, key turning points, and analyze the impact of different choices on the final narrative result in multi-scenario contexts, based on current plot clues, character personality settings, and potential contradictions.

Continuous Scene Reasoning focuses on the ability to model the spatial correlation between scenes, changes in environmental states, and the logic of information transmission. It tests the model's ability to infer the relationships between different scenes, integrate key information scattered across multiple scenes, and analyze the impact of scene changes on character behaviors or event progression, from continuously switching scenes.

Multi-Character Interaction Reasoning focuses on the ability to model goal conflicts, interest correlations, and interaction strategies among multiple subjects. It tests the model's ability to infer the core goals and potential demands of each character, analyze the cooperative or conflicting interest relationships between characters, and interpret the underlying motivations behind complex interactive behaviors, based on the dialogue content, behavioral performances, and historical interaction records of multiple characters.

A.2 Task Difficulty

Based on the experimental data in Table 1, Table 2, and Table 7, it can be found that: among the core task types of single-choice questions and open-ended questions, the scene understanding task is the most difficult, while the anomaly detection and event reasoning tasks also present certain challenges. Further analysis by question type shows that: in the context of open-ended questions, temporal reasoning is the most difficult task type, followed by the anomaly detection task in terms of difficulty; in the context of multiple-choice questions, the difficulty coefficient of the continuous scene reasoning task reaches the highest level. This result indicates that the current model still has significant limitations in its reasoning ability when dealing with dynamically switching continuous scenes, which is a key direction that requires focused breakthroughs in subsequent optimizations.

B Data Source

The CMDAR Metadata Movie Collection includes 500 carefully selected Chinese films, covering a wide range of genres and themes. It is designed to construct complex and dynamic scenarios, so as to meet the requirements of multi-threaded narratives and high production standards. Below is a detailed statistical breakdown of the collection. The 500 films in the CMDAR Metadata Movie Collection are categorized by common film genres and themes, with the statistical data presented in the Table 5.

The CMDAR Metadata Movie Collection has the following characteristics:

- **Openness:** The film content is rich and diverse, covering various genres and themes, which provides a broad perspective for research.
- **High Entropy:** The film plots are complex, involving multiple possibilities and uncertainties, which increases the complexity of the data.
- **Long Temporal Sequence:** Films typically span a long time period, enabling the portrayal of character growth and event development.
- **Strong Causality:** There are clear causal relationships between plots and events in the films, which facilitates the analysis and understanding of complex dynamic scenarios.

This data provides a solid foundation for the construction of the CMDAR benchmark and also offers abundant resources for relevant research.

C Prompt of Evaluation

D Prompt of Data construction pipeline

E Manual Screening Criteria

During the process of manual review, we set strict screening standards to ensure the high quality and consistency of the data.

Question Screening Criteria

- The grammar is correct, the wording is accurate, and there are no spelling errors. Ambiguous or easily misunderstood words should be avoided. The question must be logical in its expression, with all parts reasonably connected.
- The question must closely adhere to the theme and task scope set by the benchmark.
- The question should conform to the actual user questioning habits and context of the specific application scenario.
- Strictly check whether the question contains words such as "video" or "description".

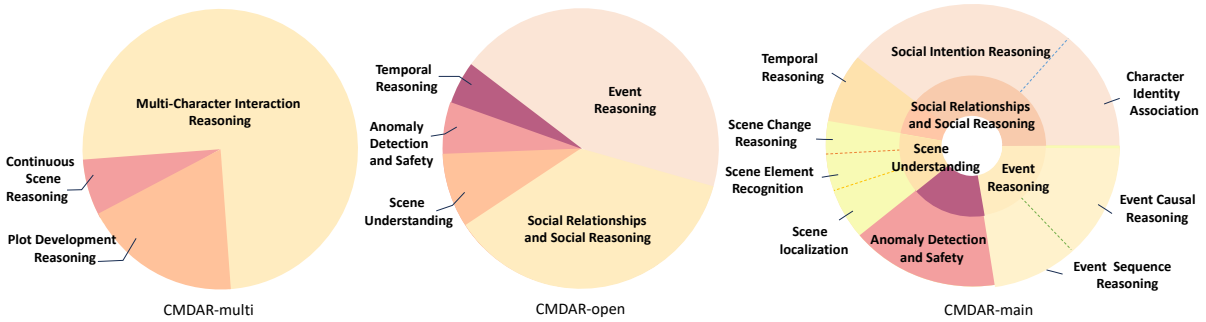

Figure 5: **Distribution** of all types of tasks included in the three benchmark tests illustrates the diversity and complexity of CMDAR tasks.

	Types	Number
11 types of films	Horror	10
	Comedy	73
	Martial Arts/Action	48
	Animation	44
	Romance	94
	Sci-Fi	12
	War	25
	Suspense/Crime	88
	Inspirational Drama	62
	Period Drama	14
	Other	30
	Total Films	500

Table 5: Data Statistics of metadata

- Delete or modify QA pairs that violate the specified requirements to ensure that the questions are concise and clear.

Answer Screening Criteria

- The answer must correspond to objective facts, and for questions with clear factual basis, the answer must be accurate.
- The logical reasoning process of the answer must be correct, without any contradictions.
- For open-ended questions, the answer should provide sufficiently rich content. Check whether the answer contains words such as "video" or "description," as these are not allowed.
- The structure of the answer should be reasonable, with clear point-by-point responses and a complete structure.

Overall QA Pair Screening Criteria

- Consistency between the question and the answer; the answer must be a direct response to the question and not be off-topic.
- If there are multiple related QA pairs, these QA pairs must maintain consistency in content and logic.
- The quality of QA pairs should be relatively stable, avoiding situations where some QA pairs are of high quality while others are not. Check whether the answer contains words such as "video" or "description," as these are not allowed.
- Conduct random sampling or comprehensive checks of QA pairs to ensure that each pair meets the screening criteria.

F Detailed Information of the Evaluated Models

In this section, we provide a detailed description of the models we selected, the models we did not

Prompt template for open-ended question answer scoring.

System:
"You are a helpful and precise assistant for checking the quality of the answer."
"[Detailed Audio Description][Audio]"
"[Question][Question]"
"[The Start of Assistant 1s Answer][Assistant1]"
"[The End of Assistant 1s Answer]"
"[The Start of Assistant 2s Answer][Assistant2]"
"[The End of Assistant 2s Answer]"
"[System]"
"We would like to request your feedback on the performance of two AI assistants in response to the user question "
"and audio description displayed above. AI assistants are provided with detailed audio descriptions and questions."
"Please rate the helpfulness, relevance, accuracy, and comprehensiveness of their responses. "
"Each assistant receives an overall score on a scale of 1 to 10, where a higher score indicates better overall performance. "
"Please output a single line containing only two values indicating the scores for Assistant 1 and 2, respectively. "
"The two scores are separated by a space."

Assistant:
{response}

Detailed explanation of the grading criteria. refer to AIR-Bench (Yang et al., 2024)

System:
"helpfulness": "Whether the response is helpful to the user and whether it can solve the user's problem"
"relevance": "Whether the response is related to the question and audio content"
"accuracy": "The accuracy of the response, whether it is factual"
"comprehensiveness": "The comprehensiveness of the response, whether it covers all aspects of the question"
"score range": "1-10 points, the higher the score, the better the performance"
"output format": "Output a line containing two scores, separated by a space"
Assistant:
{response}

Prompt of Data Generation in CMDAR-main

System:
You are a helpful AI assistant, designed to provide useful QA pair to customers. The user will provide you with a video, audio, audio translation, audio description, and video description. Please refer to this desired output and provide your own unique response.

User: Based on the provided video, audio, audio translation, audio description, and video description, create three questions about the audio. These should be three audio reasoning questions with options and answers.

The audio translation is [**audio translation**], the audio description is [**audio description**], and the video description is [**video description**].
The questions must meet **the following criteria**:
1.They should be reasoning questions related to the audio.
2.The category of the questions should fall into one of the following: temporal reasoning task, social intent reasoning task, anomaly detection and safety task, and specify which category it belongs to.
3.The posed questions should include a thought chain explanation.
4.The questions cannot be answered solely by the text of the title, they must require reasoning based on both the question and the audio.
5.The questions should introduce some additional reasoning information that does not exist in the audio to increase difficulty.
6.Various information from the audio should not appear directly in the question text; just pose the question.
7.The answers provided should follow this format: Question:..... Question Category:..... Question Options:..... Question Answer:.....

Assistant:
{response}

Prompt of Data generation in CMDAR-multi

System:
You are a helpful AI assistant, designed to provide useful answer to customers. The user will provide you with a video, audio, audio translation, audio description, and video description. Please refer to this desired output and provide your own unique response.

User: Based on the two provided relevant audio segments along with their respective translations, descriptions, and video descriptions, formulate multiple-choice audio reasoning questions-options-answers-reasoning chains for the audio pair.

Audio translation 1 is [**audio translation 1**], audio description 1 is [**audio description 1**], video description 1 is [**video description 1**], audio translation 2 is [**audio translation 2**], audio description 2 is [**audio description 2**], video description 2 is [**video description 2**].

The questions must meet **the following criteria**:

1. The question must relate to audio pairs and cannot include any information or terms related to the video.

2. The category of the question should belong to one of the following categories, and the category must be specified: continuous scene reasoning task, multi-character interaction reasoning task, plot development reasoning task, anomaly detection and security task, time reasoning task.

3. The question should not have an answer that can be derived solely from the text title; it should require reasoning that combines the question and the audio.

4. The question should involve multi-step reasoning and be challenging, with options of moderate length for the answers.

5. The multiple-choice answers can independently reason for each audio's description but must include at least one reasoning question that is related to both audio segments simultaneously.

6. Your provided answers must conform to the following format: Question:..... Question Category: ..... Question Options: ..... Question Answer: ..... Question Reasoning Chain: .....

Assistant:
{response}

Prompt of Data generation in CMDAR-open

System:
You are a helpful AI assistant, designed to provide useful answer to customers. The user will provide you with a video, audio, audio translation, audio description, and video description. Please refer to this desired output and provide your own unique response.

User: Propose an open-ended question for audio based on the given video, audio, audio translation, audio description, and video description. The requirement is an open-ended reference answer thought chain pair, where the audio translation is [**audio translation**], the audio description is [**audio description**], and the video description is [**video description**].

At the same time, the questions raised must meet **the following requirements**:

1. The requirements are only open-ended reasoning questions related to audio, and the video and provided text are only for reference in question setting and cannot be used for question setting (already questions, answers) and thought chain analysis. The questions can only be answered by understanding and reasoning about the audio.

2. The category of the question belongs to one of the following categories, and indicate which task it belongs to: time reasoning task, scene understanding task, character relationship and social reasoning task, event reasoning task, anomaly detection and security task.

3. The answer to the question cannot be found solely from the text question, it needs to be combined with the question and audio for reasoning.

4. The answer to an open-ended question is not unique, just provide a reference answer. The answer you provide should meet the following format: Question: .... Question Category: .... Reference answer: ....

Assistant:
{response}

	Statistics	Number
CMDAR-main	Total Questions	1500
	Task	5
	Sub task	9
	Average question length	30.68
	Average option length	18.69
	Average audio length	25.11
CMDAR-open	Total Questions	500
	Task	5
	Average question length	41.47
	Average reference length	175.53
	Average audio length	25.14
CMDAR-multi	Total Questions	1000
	Task	3
	Average question length	32.80
	Average answer length	47.19
	Average audio length	69.90
	Average answer number	2.82

Table 6: **Statistical information** of the three benchmark tests indicates the complexity of the benchmarks through the longer duration of the audio and the rich semantic information.

select, and the implementation details, so as to ensure reproducibility.

F.1 Evaluated Models

- Qwen2-Audio-Instruct (Chu et al., 2024) is a new series of Qwen large audio-language models. It can accept inputs of various audio signals and perform audio analysis based on voice instructions or generate direct text responses. In this paper, we use the 7B Instruct model.

- Qwen-Audio-Chat (Chu et al., 2023) is a Large Audio Language Model developed by Alibaba Cloud. It can take multiple types of audio (including human speech, natural sounds, music, and singing voices) and text as inputs, and generate text as output, supporting a multi-task learning framework for various complex audio tasks.

- Audio Flamingo 2 (Ghosh et al., 2025) possesses advanced audio understanding and reasoning capabilities. In particular, it has professional audio reasoning ability and can understand long audio clips up to 5 minutes in duration.

- Audio Flamingo 3 (Goel et al., 2025) (AF3) is a fully open-source, state-of-the-art Large Audio Language Model (LALM), which consists of an AF-Whisper unified audio encoder, an MLP-based audio adapter, a decoder-only LLM backbone (Qwen2.5-7B), and a streaming TTS module (AF3-Chat). Audio Flamingo 3 can accept audio inputs with a duration of up to 10 minutes.

- Audio Flamingo 3 Chat. As the chat version of Audio Flamingo 3, it is capable of voice chat and multi-audio dialogue.

- Kimi-Audio-Instruct (KimiTeam et al., 2025) is designed as a general-purpose audio foundation model, which can handle a wide range of audio processing tasks within a single unified framework. It adopts mixed audio inputs (continuous acoustic signals + discrete semantic tokens) and an LLM core with parallel heads for text and audio token generation.

- Omni-R1 (Zhong et al., 2025) is an all-modal model that addresses the resolution issue through a dual-system architecture. Meanwhile, it proposes an end-to-end RL framework—Omni-R1 is built on Group Relative Policy Optimization (GRPO). The results demonstrate the first successful applica-

Prompt of Interference option generation

System:
You are a helpful AI assistant, designed to provide useful answer to customers. The user will provide you with a video, audio, audio translation, audio description, and video description. Please refer to this desired output and provide your own unique response.

User: Based on the given QA pair (question and correct answer) and audio, video descriptions, and audio descriptions, generate 3 high-quality distractor options.

the audio translation is [**audio translation**], the audio description is [**audio description**], and the video description is [**video description**].

The distractor options should possess **deception** (appearing reasonable from a surface logic or common sense perspective, easily causing those who lack key information to misselect), **relevance** (closely adhering to the question theme without deviating from the core scene/field), and **incorrectness** (clearly contradicting the correct answer or contradicting the facts in the background information), ultimately forming a complete set of multiple-choice options consisting of "1 correct answer and 3 distractor options".

Assistant:
{response}

tion of RL in large-scale all-modal reasoning and highlight a scalable path toward general-purpose foundation models.

- R1-AQA (Li et al., 2025) is an Audio Question Answering (AQA) model optimized through reinforcement learning using the Group Relative Policy Optimization (GRPO) algorithm.

- SALAMONN (Tang et al., 2024) is a Large Language Model (LLM) that supports speech, audio event, and music inputs, developed by the Department of Electronic Engineering of Tsinghua University and ByteDance. It can perceive and understand various types of audio inputs. In this paper, we use the 7B version.

- Audio-Reasoner (Xie et al., 2025) is an open-source project developed by a team from Tsinghua University, focusing on building a large language model that supports in-depth audio reasoning. Based on Qwen2-Audio-Instruct, this model incorporates structured chain-of-thought technology to achieve complex reasoning and multi-modal understanding of audio content.

- DeSTA2.5-Audio (Lu et al., 2025) is a general-purpose Large Audio Language Model (LALM) designed for robust auditory perception and instruction-following capabilities, without the need for task-specific audio instruction tuning.

- MiDashengLM (Dinkel et al., 2025) integrates the powerful Dasheng audio encoder with the Qwen2.5-Omni-7B Thinker decoder through a unique caption-based alignment strategy.

- GPT-4o Audio is a multi-modal speech interaction model launched by OpenAI. It not only supports mixed input and output of text and audio but also achieves multiple technological breakthroughs in emotion recognition, real-time response, speech synthesis, and other aspects. It is a representative closed-source speech model in the current first-tier category.•

- Qwen2.5-Omni (Xu et al., 2025a) is an end-to-end multi-modal model designed to perceive multiple modalities, including text, images, audio, and video, while generating text and natural speech responses in a streaming manner.

All models are used in inference mode only, with code and settings consistent with the official inference code, and a temperature value of 0 , max length is 256.

F.2 Unselected Models

- Mellow (Deshmukh et al., 2025) is a small audio language model specifically designed for reasoning. In our experiments, this model does not possess Chinese language capabilities.

- GAMA (Ghosh et al., 2024a) is a large audio language model that combines advanced audio understanding and complex reasoning capabilities. Its core technical highlight lies in its unique model architecture and data processing method. In our experiments, this model does not possess Chinese QA (Question Answering) capabilities.

G Detailed results of CMDAR-multi

In Table 7, the detailed results of each subtask of CMDAR-multi are clearly visible, which undoubtedly provide highly convincing evidence for the argument regarding the difficulty of the CMDAR benchmark and the difficulty of each subtask.

H Option Distribution and Instruction Bias

In multiple-choice tasks, the distribution of options and the phrasing of instructions often have a significant impact on the model's selection behavior. If the distribution of option quantities is uneven, or if certain options appear significantly more frequently in the training data, the model may tend to select these high-frequency options, leading to an overestimation or bias in performance. Additionally, the way instructions are phrased can also significantly affect the model's reasoning results.

To avoid these biases, we ensure balanced option distribution, mutually exclusive option content, and clear semantics in the benchmark design, and when necessary, we randomize the order of options to reduce the influence of instruction prompts on model outputs. In terms of instruction selection, we tested four different instruction prompts, and the results are shown in the table 11. Ultimately, we adopted the instruction that yielded the best results, ensuring the correct outputs and reviews for the vast majority of models.

I Case study

In order to better analyze the model's performance on different tasks, we conducted a qualitative study of the model's prediction results. This section uses specific examples to demonstrate common types of failures, differences in task performance, and sources of errors, helping us understand the model's limitations and areas for improvement in real-world scenarios.

I.1 Tasks cases

To explore the challenges posed by different task types on the model, we further present cases in a multi-task scenario (cases in Table 8 and Table 9). The results indicate that the model performs well on structured question answering and simple classification tasks, but its performance significantly declines in tasks that require multi-step reasoning, cross-modal integration, or in real-world data containing noise. This suggests that the current model's generalization ability is still constrained by the distribution of the training data, posing challenges to cross-task transfer capabilities.

I.2 Errors cases

Table 10 summarizes the distribution of error types, including perception errors, reasoning errors, knowledge loss, and formatting errors. Our analysis shows that the highest proportion of inference errors is mainly manifested in the breakage of the multi-step reasoning chain, errors in causal judgment and insufficient integration of contextual information. Perceptual errors often occur in the case of noise or multiple speaker interference, and factual errors caused by lack of knowledge cannot be ignored, while format errors reflect the weakness of the model in output constraints and normalization.

Model	Size	Type	EM(%)			JI(%)		
			PDR	CSR	MCIR	PDR	CSR	MCIR
Qwen2-Audio-Instruct	7B	LALM	2.08	4.42	0.00	26.48	22.33	12.93
Qwen-Audio-Chat	8.4B	LALM	7.29	6.28	0.00	48.06	42.23	38.45
Qwen2.5-Omni	3B	OLMs	18.75	26.96	17.24	50.78	59.31	49.71
Qwen2.5-Omni	7B	OLMs	25.00	27.10	27.59	54.50	58.80	49.43
GPT-4o Audio	-	LALM	**52.08**	**51.36**	**62.07**	**72.40**	**74.16**	**80.17**
GPT-4o mini Audio	-	LALM	18.75	21.11	39.29	49.05	53.22	67.86
DeSTA2.5-Audio	8B	LALM	14.58	15.69	10.34	41.41	45.45	43.39
Kimi-Audio-Instruct	7B	LALM	12.50	16.26	13.79	47.92	45.67	47.70
MiDashengLM	7B	LALM	11.46	8.42	6.90	42.92	38.83	27.01
Omni-R1	7B	OLMs	6.25	3.28	3.45	46.49	46.21	43.97
R1-AQA	7B	LALM	1.04	2.71	0.00	12.50	15.50	8.91
Model	**Size**	**Type**	**Precision(%)**			**Recall(%)**		
			PDR	**CSR**	**MCIR**	**PDR**	**CSR**	**MCIR**
Qwen2-Audio-Instruct	7B	LALM	32.48	28.85	22.41	34.90	28.22	16.67
Qwen-Audio-Chat	8.4B	LALM	53.00	47.45	44.20	64.84	56.67	54.02
Qwen2.5-Omni	3B	OLMs	73.09	80.35	72.70	54.34	62.80	52.87
Qwen2.5-Omni	7B	OLMs	73.51	81.45	67.82	57.38	61.85	50.00
GPT-4o Audio	-	LALM	**78.65**	**84.44**	85.92	**77.26**	**77.72**	**83.91**
GPT-4o mini Audio	-	LALM	67.01	73.18	**88.10**	51.82	55.31	70.24
DeSTA2.5-Audio	8B	LALM	55.47	62.59	63.79	47.05	51.13	48.85
Kimi-Audio-Instruct	7B	LALM	69.97	68.12	65.80	53.47	49.26	53.45
MiDashengLM	7B	LALM	51.60	49.32	42.82	52.60	49.04	35.06
Omni-R1	7B	OLMs	51.20	51.17	45.98	62.50	63.85	60.92
R1-AQA	7B	LALM	18.58	22.42	11.78	14.41	18.77	13.22

Table 7: Detailed results for each category of CMDAR-multi. The best results are highlighted in **bold** and the second-best is underlined.

Tasks	Question and Option	Answer
Scene Understanding	问题：综合分析音频中的各种声音元素，该场景最有可能发生在哪里？选项：["一个播放着欧美流行乐的西式快餐厅","一个提供自助餐并播放传统音乐的员工餐厅","一个正在举办婚礼、人声鼎沸的中式酒楼","一个安静的、仅提供素食的私人会所"],	"一个提供自助餐并播放传统音乐的员工餐厅"
Social Relationships and Social Reasoning	问题：综合音频，以下哪种场景最贴切地描述了对话双方的身份和所处情境？选项：["一位导演正在指导演员，并对她的表演提出反馈","两位专业的配音演员在录音棚里对稿，背景音乐是配乐样本","一位表演系学生正在家中练习台词，她的朋友或伴侣在一旁听着","一对情侣在一家有现场钢琴演奏的高档餐厅里进行深刻的情感交流"]	"一位表演系学生正在家中练习台词，她的朋友或伴侣在一旁听着"
Event Reasoning	问题：结合音频推断对话发生的直接原因最可能是什么？选项：["一名男性因工作压力过大而临时约朋友倾诉","一名男性因家庭矛盾冲动离家后偶遇老友","一名男性因目睹交通事故后情绪崩溃寻求安慰","一名男性因回忆触发痛苦往事而躲进童年避难所"]	"一名男性因回忆触发痛苦往事而躲进童年避难所"
Temporal Reasoning	问题：根据音频推断出此次抢救大约是从何时开始的？选项：["晚上20点45分","晚　上21点08分","晚上21点30分","晚上20点55分"]	"晚上21点08分"
Anomaly Detection and Safety	问题：结合音频可以推断出当前任务最显著的特点是什么？选项：["任务已成功完成，正在进行事后汇报","任务规划存在重大分歧，团队正在激烈争论","这是一个演习场景，电子音是模拟结束的信号","任务具有极高的时间敏感性和风险，可能正处于倒计时阶段"]	"任务具有极高的时间敏感性和风险，可能正处于倒计时阶段"

Table 8: Case of each tasks in CMDAR-main

Tasks	Question and Option	Answer
Plot Development Reasoning	问题："综合两段音频中的对话和情境，可以对人物关系和核心情节做出哪些合理的推断？"选项：["在第一段音频中，女性角色指控男性角色的动机是，万文芳发现了该男性并非其亲生儿子万思臣，因此他杀人灭口","两段音频中的核心冲突是围绕一份亲子鉴定展开的，该鉴定是为了证明男性角色是女性角色的亲生父亲，以此来承担责任","第二段音频中提到的“亲子鉴定”很可能是对第一段音频中“你不是万思臣”这一指控的决定性验证，这份结果将证实男性的真实身份","从第一段音频中女性的质问“这不是你的复仇计划吗”可以推断，她承认了谋杀案是自己策划的，目的是为了向男性复仇"]	["在第一段音频中，女性角色指控男性角色的动机是，万文芳发现了该男性并非其亲生儿子万思臣，因此他杀人灭口","第二段音频中提到的“亲子鉴定”很可能是对第一段音频中“你不是万思臣”这一指控的决定性验证，这份结果将证实男性的真实身份"]
Continuous Scene Reasoning	问题：结合两段音频，关于这场冲突的规模和发展，可以得出哪些合理的推断？选项：["音频1中，沉重的撞击声和持续的坍塌声暗示了冲突可能发生在一座大型建筑或城墙附近，且该结构正在遭受猛烈攻击","音频2中的密集爆炸声和混乱的金属碰撞声，相比于音频1，表明冲突进入了更白热化、更混乱的近距离交战或轰炸阶段","综合两段音频，战斗的规模宏大，不仅限于小队交火，而是涉及了大规模杀伤性力量的全面战争","从音频1到音频2，冲突的强度明显减弱，声音从大规模破坏转为零星的个人战斗，表明战斗已接近尾声"]	["音频1中，沉重的撞击声和持续的坍塌声暗示了冲突可能发生在一座大型建筑或城墙附近，且该结构正在遭受猛烈攻击","音频2中的密集爆炸声和混乱的金属碰撞声，相比于音频1，表明冲突进入了更白热化、更混乱的近距离交战或轰炸阶段","综合两段音频，战斗的规模宏大，不仅限于小队交火，而是涉及了大规模杀伤性力量的全面战争"]
Multi-Character Interaction Reasoning	问题：综合两段音频，以下关于两位说话者互动动态的推断，哪些是合理的？选项：["在第一段音频中，年长者提及泡澡的回忆，其语气透露出他希望通过共同的过去来缓和当前略显紧张和尴尬的气氛","在第二段音频中，年长者讲述了更具体、甚至有些尴尬的童年趣事，这表明他可能在试探年轻人的真实反应，而不仅仅是单纯地怀旧","综合两段音频，年轻人从始至终以平淡、疏远的语气回应“不记得”，这种一致性暗示他的“遗忘”可能并非简单的记性不好，而是一种刻意的情感疏离或心理防御","两段音频整体氛围轻松愉快，对话显示两人正在愉快地分享童年糗事，关系非常融洽"]	["在第一段音频中，年长者提及泡澡的回忆，其语气透露出他希望通过共同的过去来缓和当前略显紧张和尴尬的气氛","在第二段音频中，年长者讲述了更具体、甚至有些尴尬的童年趣事，这表明他可能在试探年轻人的真实反应，而不仅仅是单纯地怀旧","综合两段音频，年轻人从始至终以平淡、疏远的语气回应“不记得”，这种一致性暗示他的“遗忘”可能并非简单的记性不好，而是一种刻意的情感疏离或心理防御"]

Table 9: Cases of each tasks in CMDAR-multi

Errors	Question and Option	Answer	Output
Perception Errors	问题：根据音频，对话最可能发生在以下哪个场景？选项：["喧闹的警察局大厅","作为临时据点的室内空间","车辆疾驰的马路边","人声鼎沸的露天夜市"],	"作为临时据点的室内空间"	"人声鼎沸的露天夜市"
Reasoning Errors	问题：根据音频对话，可以推断出两位对话者的身份关系最可能是什么？选项：["图书管理员与一位正在抱怨的读者","一起处理新到货物的同事","正在进行安全演练的师生","送货员与负责签收的职员"]	"一起处理新到货物的同事"	根据音频对话中的内容，可以听到对话涉及“新到的书”，同时还提到了“分类”这样的词汇。这些关键词很可能与图书馆的场景相关。因此，两位对话者的关系最可能是“图书管理员与一位正在抱怨的读者”。
Knowledge Gaps	问题：这段欢快的音乐最有可能出现在以下哪个节日的庆祝活动中？选项：["日本的盂兰盆节","巴西的狂欢节","美国的阿巴拉契亚民俗音乐节","西班牙的弗拉明戈艺术节"]	"美国的阿巴拉契亚民俗音乐节"	"巴西的狂欢节"
Formatting Errors	问题：综合音频，最有可能是什么事件刚刚发生，从而引发了第一位说话者的这段言论？选项：["他刚刚阅读完一份冗长乏味的历史文献","有人刚刚完成了一次迅猛如风、精准无比的箭术或剑术展示","一位异国使者刚刚带着和平条约抵达","太阳刚刚升起，照亮了一片壮丽的风景"]	"有人刚刚完成了一次迅猛如风、精准无比的箭术或剑术展示"	"有人刚刚完成了一一次迅猛如风，精准无比的箭术或剑术展示"

Table 10: Cases of each errors

	Prompt	Qwen2-Audio -Instruct	Omni-R1	Qwen2.5-Omni	R1-AQA
v1	$choices_{str} = "\backslash \mathbf{n}"$ $.join(item["chosens"])$ $item["question"]+$ 选项如下**:** $+choices_{str}+$ 选择正确的选项。	17.93	37.29	36.13	26.13
v2	$choices_{str} = "\backslash \mathbf{n}"$ $.join(item["chosens"])$ $item["question"]+$ 选项如下**:** $+choices_{str}+$ 请直接给出正确选项的内容。	24.13	43.83	76.27	29.00
v3	$choices_{str} = "\backslash \mathbf{n}"$ $.join(item["chosens"])$ $item["question"]+$ 请从下列选项中选择正确的选项。 $+choices_{str}$	14.33	21.01	26.00	23.07
v4	$choices_{str} = "\backslash \mathbf{n}"$ $.join(item["chosens"])$ $item["question"]+$ 请从下列选择中直接给出正确选项的内容: $+choices_{str}$	22.00	18.55	73.67	24.93

Table 11: Average accuracy of multiple-choice questions using four models with different prompts