

VocalBench: Benchmarking the Vocal Conversational Abilities for Speech Interaction Models

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Abstract

The rapid advancement of large language models (LLMs) has accelerated the development of multi-modal models capable of vocal communication. Unlike text-based interactions, speech conveys rich and diverse information, including semantic content, acoustic variations, paralinguistic cues, and environmental context. However, existing evaluations of speech interaction models predominantly focus on the quality of their textual responses, often overlooking critical aspects of vocal performance and lacking benchmarks with vocal-specific test instances. To address this gap, we propose VocalBench, a comprehensive benchmark designed to evaluate speech interaction models' capabilities in vocal communication. VocalBench comprises 9,400 carefully curated instances across four key dimensions: semantic quality, acoustic performance, conversational abilities, and robustness. It covers 16 fundamental skills essential for effective vocal interaction. Experimental results reveal significant variability in current model capabilities, each exhibiting distinct strengths and weaknesses, and provide valuable insights to guide future research in speech-based interaction systems.

1 Introduction

Recent breakthroughs in large language models (LLMs) have revolutionized natural language understanding and generation, extending their capabilities from text-only interactions to multi-modal communication, including speech (Ji et al., 2024). Speech-based interaction offers a richer and more natural interface than text, as it inherently conveys diverse layers of information such as semantic content, acoustic nuances, paralinguistic signals, and environmental context. Despite this promise, some existing speech interaction systems follow a cascade design, chaining automatic speech recognition (ASR) and text-to-speech (TTS) modules to bridge spoken input and output (Shen et al., 2023; An

et al., 2024; Huang et al., 2024). While effective in delivering fluent vocal exchanges, these modular pipelines suffer from several critical drawbacks: they ignore subtle paralinguistic cues essential for natural communication and introduce latency that impairs real-time interaction.

To address these limitations, end-to-end speech interaction models have emerged. By integrating speech encoders that discretize raw audio signals with vocoders for speech synthesis, these systems enable LLMs to process and generate speech directly, bypassing intermediate text representations (Fang et al., 2024; Wang et al., 2024, 2025b). This paradigm shift is further accelerated by the rise of omni-modal LLMs equipped with specialized encoders for images and videos (Li et al., 2025; OpenBMB, 2025; Xu et al., 2025), all maintaining vocal interaction as a core capability. Such integrated architectures promise more coherent, context-aware, and natural vocal communication.

On the other hand, the rapid progress in LLM evaluation has yielded unified frameworks assessing diverse capabilities (Hendrycks et al., 2021; Suzgun et al., 2023; Du et al., 2025). Despite these advances, systematic evaluation of speech interaction models remains severely underdeveloped, and existing benchmarks focus almost exclusively on text outputs. As illustrated in Figure 1, speech interaction models must excel not only in semantic understanding but also in producing speech responses with natural acoustic qualities, fluent and efficient conversations, and robustness against noisy or adverse acoustic environments. Current speech evaluation benchmarks (Yang et al., 2024; Chen et al., 2024b; Li et al., 2025) suffer from critical limitations: (1) evaluation primarily targets speech-to-text transcription accuracy, neglecting speech generation quality; (2) insufficient measurement of speech naturalness, expressiveness, and paralinguistic factors; (3) ambiguous or narrow ability categorization failing to reflect the multi-

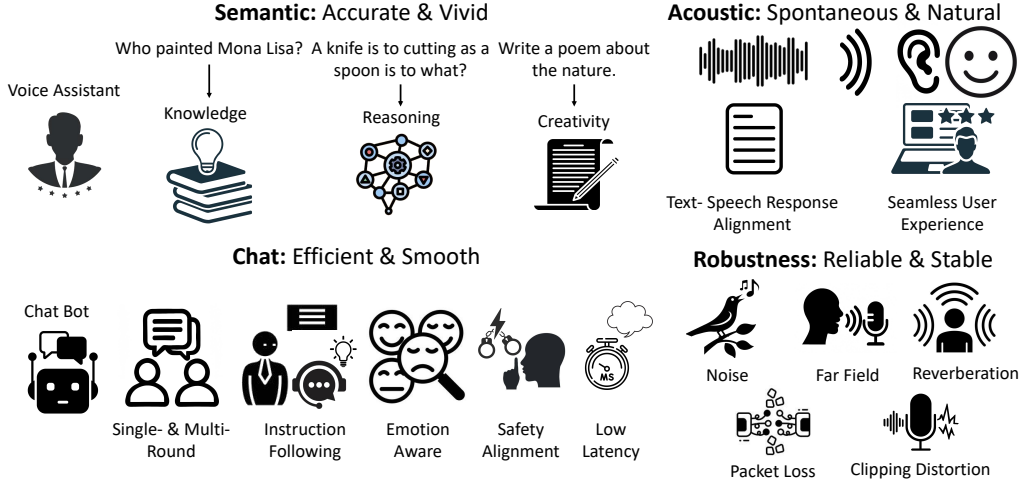


Figure 1: Key ability dimensions of speech interaction models.

faceted nature of vocal communication; and (4) a lack of speech-specific, real-world conversational scenarios. These deficiencies severely limit our ability to understand and improve the full spectrum of speech interaction capabilities.

In response, we propose VocalBench, the first large-scale, multi-dimensional benchmark specifically designed to rigorously quantify the vocal conversational abilities of speech interaction models. VocalBench encompasses 9,400 carefully curated instances covering a comprehensive set of capabilities: general knowledge, reasoning, creativity, emotional empathy, single- and multi-turn dialogue, safety alignment, instruction following, acoustic speech quality, and robustness under challenging acoustic conditions. Beyond prior benchmarks, VocalBench uniquely incorporates speech-specific conversational scenarios, including emotionally charged dialogues and responses conditioned on speaking style and attributes, thus closely mirroring real-world vocal communication demands. Our contributions can be summarized as follows:

- We introduce VocalBench, the most comprehensive and systematic evaluation framework that holistically assesses both the linguistic and acoustic dimensions of speech interaction models, filling a critical gap in the field.
- We conduct extensive experiments on a diverse set of state-of-the-art open-source speech interaction models, ranging from lightweight LLM backbones with fewer than 1 billion parameters to mid-scale models around 7 billion parameters. Our fine-grained evaluations reveal each model’s distinct strengths

and weaknesses, offering actionable guidance for future research and practical development.

2 VocalBench Overview

As shown in Table 1, VocalBench consists of evaluations on 4 dimensions and 16 abilities. For the semantic dimension, VocalBench is divided into 3 basic tasks related to knowledge, reasoning and creativity abilities. The acoustic performance is evaluated using UTMOS (Saeki et al., 2022), a widely adopted MOS predictor, and word error rate (WER) to quantify the alignment of response in text and speech modalities. For speech interaction models, the text response is regarded as transcription, and the transcribed speech response should be consistent with its corresponding text response. The calculation is performed on the single-round set in the chat dimension for cost reduction, and the chat dimension of VocalBench contains another four abilities: multi-round conversation, instruction following, emotion-aware and safety alignment. A latency estimation is conducted by computing the real-time factor (RTF) on the single-round set. In terms of robustness evaluation, VocalBench refers to VoiceBench (Chen et al., 2024b) and conducts experiments on two types of noise, reverberation, far-field, packet loss, and clipping distortion.

In order to achieve more detailed ability assessment, we also provide multi-granular annotations, such as topics in knowledge tests, and categories of questions in reasoning and creativity. The sample questions of each type is listed in Appendix F. In the semantic dimension, we have chosen the sample with the best speech quality in seed_tts (Anastas-

Dimension	Ability	Statics				Source	Evaluation Method / Indicator
		Category	Instances	Reference	Annotation		
Semantic	Knowledge	13	2000	✓	Topic	LLaMA-Q, SciQ, Web-Q, TriviaQA	Accuracy
	Reasoning	8	1000	✓	Category	CommonsenseQA, gsm8k, STORAL, LLM-generated, self-made	LLM Eval
	Creativity	6	400	✓	Category	Web, LLM-generated, self-made	LLM Eval
Acoustic*	Fluency	-	-	-	-	Single-round Set	UTMOS
	Clarity	-	-	-	-	Single-round Set	WER
Chat	Single-round	2	200	✓	Category	AlpacaEval, LLM-Generated, self-made	LLM Eval
	Multi-round	13	400	✓	Category	mt-bench-101	LLM Eval
	Instruction Following	16	900	✗	Category, Sub-category	FollowBench, SpeechInstructBench, etc.; LLM-generated, self-made	Following Rate
	Emotion Aware	5	500	✗	Question_emo etc.	LLM-generated, self-made	Semantic + Acoustic Score
	Safety Alignment	1	400	✓	Category	SafetyTraining (test)	Refusal Rate
	Latency*	-	-	-	-	Single-round Set	RTF
Robustness	Noise	2	1200	✓	Category, Severeness	Single-round Set	LLM Eval, Preserve Rate
	Reverberation	1	600	✓	Category, Severeness	Single-round Set	LLM Eval, Preserve Rate
	Far-field	1	800	✓	Category, Severeness	Single-round Set	LLM Eval, Preserve Rate
	Packet Loss	1	500	✓	Category, Severeness	Single-round Set	LLM Eval, Preserve Rate
	Distortion	1	500	✓	Category, Severeness	Single-round Set	LLM Eval, Preserve Rate
Total		-	9400	-	-	-	-

* The evaluation of the acoustic dimension and latency calculation is conducted on the single-round set.

Table 1: The division of dimensions and abilities and general statistics of VocalBench.

siou et al., 2024) as the prompt for zero-shot speech synthesis to ensure the clarity and naturalness of the speech query, minimizing interference from poor speech queries in the evaluation of these abilities. For other tasks, especially in the chat dimension, we have randomly selected speech prompts to simulate interactions in real scenarios within seed_tts and Common Voice (Ardila et al., 2020).

3 Creation Pipeline and Subset Details

The main creation pipeline of VocalBench is shown in Figure 2. Text queries are sourced from the following origins: open-source evaluation corpora, outputs generated by Qwen2.5-max¹, and self-made content. We perform speech synthesis to obtain the corresponding speech queries using CosyVoice (Du et al., 2024a), and then adopt a strict check process to ensure the quality of the evaluation instances. All speech queries are transcribed using Whisper (Radford et al., 2023), and only absolutely correct ones are kept without comparison. For the rest instances, those been recognized as words with the same pronunciation are also preserved, and those with speech errors are re-synthesized until passing the manual examination. Although CosyVoice is one of the most advanced, it has synthesis errors for special words. For necessary samples, we have disassembled the pronunciation of the word or modified it to a homophone for synthesis until it matches the correct pronunciation. For evaluation sets with additional requirements, extra examination has been introduced. For example, in the construction of the emotion-aware set, speech emotion recognition with emotion2vec_plus_large (Ma et al., 2024a) is conducted until the recognized type meets the requirement.

¹<https://qwenlm.github.io/blog/qwen2.5-max/>

The synthesized speech queries preserve details that have not been focused on in previous work, such as correct pronunciation of named entities, acronyms, numerical expressions, and speech with specific emotions. For the response side, Qwen2.5-max is utilized to generate necessary references and evaluate the semantic performance of complex questions, following Minmo (Chen et al., 2025).

3.1 Semantic Quality

Semantic quality evaluation is performed to assess the semantic accuracy and wording quality of the responses. Previous benchmarks mainly focus on the general knowledge preserved while ignoring other aspects (Li et al., 2025), and in some research, the speech queries are typically synthesized on their own, hiding a fair comparison (Défossez et al., 2024; Wang et al., 2024; Chen et al., 2025). VocalBench integrates existing knowledge assessment datasets and constructs a comprehensive evaluation corpus covering 13 topics. In addition, we have also included reasoning and literary creativity tests, which have been missing in previous evaluations.

3.1.1 General Knowledge

The possession of general knowledge is one of the important capabilities of the speech interaction models. Previous evaluations (Chen et al., 2025; Li et al., 2025) have been conducted on LLaMA Questions (Nachmani et al., 2024), Web Questions (Berant et al., 2013) and TriviaQA (Joshi et al., 2017). The experiments are typically conducted on the same text, but the lack of a speech version of the user queries prevents a fair comparison. To form a unified, comprehensive and detailed benchmark, we have selected instances from the above-mentioned corpus and also added SciQ (Welbl et al., 2017) to balance the propor-

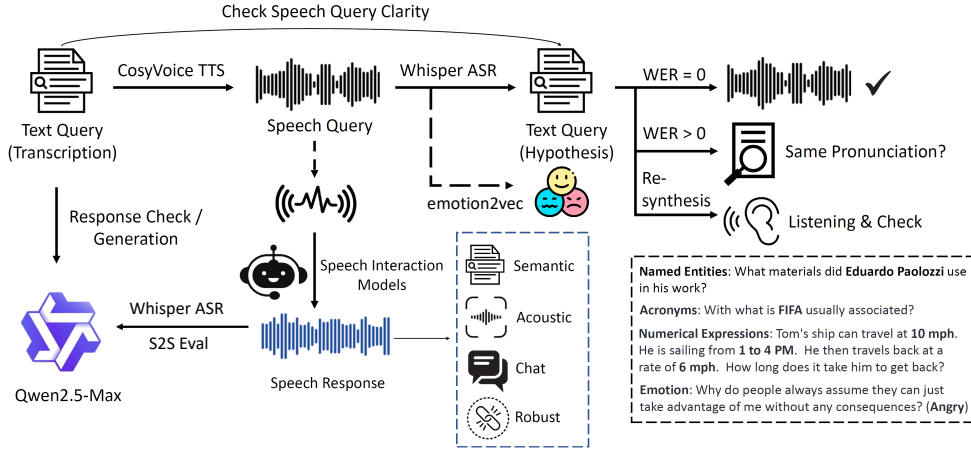


Figure 2: Main creation pipeline for VocalBench.

tion of various topics. The data processing process is as follows: 1) We first retain examples with clean and brief answers, usually presented as words or phrases; 2) We use Qwen2.5-max and detect whether its generated response contains the complete answer; 3) We conduct speech synthesis using CosyVoice and then transcribe with Whisper, and only the question whose answer within the response can be correctly recognized are preserved; 4) We use Qwen2.5-max to label the topic of each question and equilibrate the proportion of each type, resulting in a balanced general knowledge evaluation set of 2,000 instances from 13 diverse topics. The purpose of 3rd step is to ensure that the keywords would be correctly transcribed in clean speech responses, thereby mimicking speech recognition errors in the speech-to-speech (s2s) evaluation.

3.1.2 Complex Reasoning

When dealing with logical operations or mathematical queries, the speech interaction model should demonstrate steady reasoning ability to solve complex practical problems. However, reasoning evaluation is more common in the text modality, and the lack of widely adopted speech test has prevented the development of this field. We have selected 8 common reasoning types, including analogical, causal, common sense, conflicts, deductive and inductive, hypothesis, math, and story analysis. The instances are transformed into the spoken format from the source queries in CommonsenseQA (Tal-

plete manual check to ensure the quality.

3.1.3 Literature Creativity

The speech interaction model should preserve the ability to complete literary creation with specific stylistic features. Different from text modality, we have removed the evaluation of code generation and specific written formats, such as thesis, JSON, etc. The creativity evaluation of VocalBench contains four basic categories, including poem, narrative, argumentative and descriptive. In addition, we have also formed a test of appreciation, where the model is asked to explain the wonderfulness of a famous line, as well as a role-playing setting evaluation, where the question specifies two roles, and the model is instructed to play a role by speaking directional content to achieve the final purpose. This part mainly comes from the writing guidance on the website, which is obtained by rewriting into complete questions and colloquial language.

3.2 Acoustic

To evaluate the acoustic quality of speech responses, the speech interaction models are inferred in the most common conversational scenarios, which have also been used as single-round evaluation in the chat dimension. The quality of speech is measured by two indicators: UTMOS (Saeki et al., 2022) is used to measure the overall quality of speech, representing the fluency and naturalness, and WER is used to measure the consistency of generated responses of both text and speech modalities. Considering existing speech interaction models generate aligned text and speech responses, the calculation of WER is conducted to indicate the speech clarity, as cleaner speech is closer to the generated text after being transcribed.

3.3 Chat

Along with performing as a voice assistant that expert in knowledge, reasoning, and creation, speech interaction models typically need to implement chatbot functions. VocalBench systematically evaluates the model’s conversational capabilities in five typical scenarios, including single-round chat, multi-round chat, safety alignment, instruction following, and emotion aware, which refers to the ability to understand and empathize with query emotions and respond with proper tones.

3.3.1 Single Round

In the evaluation of single-round chat, VocalBench consists of two types of query formats. The suggestion queries require the models to make corresponding suggestions or detailed solutions for specific premises, while guidance queries require the explanation of the completion process of a certain routine. The test instances in this part are mainly derived from AlpacaEval (Li et al., 2023) and are presented as a set of representative interaction scenarios. They are also used to quantify the acoustic quality of the speech response and serve as the clean data for robustness testing.

3.3.2 Multi-round

In the conversational setting, the modeling of context information dramatically affects the response quality. To evaluate the multi-round chat ability of speech interaction models, we have reconstructed 400 test instances from mt-bench-101 (Bai et al., 2024). The data creation pipeline includes deleting instances with special tokens difficult to express in spoken language, text normalization, and finally covering the 13 categories divided by mt-bench-101, including context memory, content confusion, etc. The questions and answers of some samples have been simply modified to conform to common conversation scenarios. To evaluate the context incorporation ability for speech interaction models, the real text of the previous rounds is treated as context to provide correct history information.

3.3.3 Instruction Following

For interaction models, the ability to correctly understand and execute user instructions is a prerequisite for efficient communication. Unlike text modalities, in vocal interaction scenarios, there exist instructions on the paralinguistic attributes of responses, including speaking speed, emotion, etc., while almost no need for long response generation

or in special formats, such as long passages and codes. To form a comprehensive and wide-ranging instruction following evaluation set, we have borrowed the concepts, division and specific categories from InFoBench (Qin et al., 2024), IFEval (Zhou et al., 2023), FollowBench (Jiang et al., 2024) and SpeechInstructBench (Wang et al., 2025a). Referring to the division of FollowBench, VocalBench consists of subsets related to content, style, situation, format, and an additional set unique to speech interaction models - paralinguistic. There are 16 specific types of evaluation, as shown in Table 17.

3.3.4 Emotion Aware

The speech interaction model can generate customized speech responses by sensing the user’s emotions. For example, when the user is talking about a sad experience, the model should generate comforting sentences with sad emotions rather than angry, surprised or happy voices. Following the setting of Gao et al. (2025), we have selected the most common emotions - neutral, angry, happy, sad and surprised, and developed an evaluation subset with 100 instances corresponding to each emotion. A text prompt is derived from an emotional Twitter message (Saravia et al., 2018), and Qwen2.5-max is instructed to generate a user query with specific experience. For the type of “surprised”, we adopt CosyVoice 2 (Du et al., 2024b) to generate emotional speech queries and for the rest categories, we perform zero-shot speech synthesis with a random speech prompt from CREMA-D (Cao et al., 2014). The speech emotion probability is obtained by the pre-trained emotion2vec_plus_large (Ma et al., 2024b), and only the synthesized speech queries with a probability over 0.8 is preserved. To quantify the speech response quality, the emotion score consists of a semantic score generated by Qwen2.5-max, and an acoustic score calculated by considering the emotion in response speech. The calculation of the acoustic score is:

$$S_A(Emotion) = \sum_{i \in E} p_i s_i \quad (1)$$

where E is the set of the considered emotions, p_i is the emotion probability of response and s_i is the score rated by Qwen2.5-Omni corresponding to the emotional query. The overall emotion-aware score is added with the acoustic score and the semantic score in the s2s setting.

3.3.5 Safety Alignment

Safety alignment ensures the behaviour is consistent with human values, ethical norms, and safety standards. We have selected 400 instances for safety testing², covering dangerous user queries related to violent tendencies, illegal inducement, potential discrimination issues, etc. For this subset, the model should identify the user’s intentions and refuse to answer their questions or dissuade them.

3.3.6 Latency

The requirement for low latency has become a crucial factor in effective and seamless communication. Existing models usually adopt optimization solutions to improve response speed, including efficient voice active detection (VAD) to detect the query boundary, streaming decoding methods, and chunk-wise speech generation. These schemes hinder the uniform comparison because they involve excessive tradeoffs in computation time and accuracy. Instead, we report the real-time factor (RTF) for non-streaming speech generation to provide a relatively fair comparison of the computational overhead and response time of each system when generating speech responses of the same problem.

3.4 Robustness

Variations in background environments and recording conditions present a major challenge. In [Chen et al. \(2024b\)](#), the interference is categorized into far-field, clipping distortion, reverberation, packet loss and noise. Considering their evaluation set has not been released, we follow their approach to form a transparent robustness test set. We randomly select 100 instances from the single-round chat set and synthesize various acoustic environments. The data construction method is listed in Appendix B.

4 Evaluation Performance

The performance of various models on VocalBench is shown in Figure 3 and Table 2. The calculation of the overall score is list in Appendix C.

4.1 Evaluated Models

VocalBench is evaluated on 12 models. The tiny models (<1B) include Mini-Omni ([Xie and Wu, 2024a](#)), Mini-Omni2 ([Xie and Wu, 2024b](#)), SLAM-Omni ([Chen et al., 2024a](#)) and VocalNet-1B ([Wang et al., 2025b](#)). For base models (~7B), VocalBench

is evaluated on 5 speech models including LLaMA-Omni ([Fang et al., 2024](#)), Freeze-Omni ([Wang et al., 2024](#)), GLM-4-Voice ([Zeng et al., 2024](#)), Kimi-Audio ([Ding et al., 2025](#)), and VocalNet-8B, along with 3 omni models, Baichuan-Omni-1.5 ([Li et al., 2025](#)), MiniCPM-o 2.6 ([OpenBMB, 2025](#)) and Qwen2.5-Omni ([Xu et al., 2025](#)), that can handle text, speech and image inputs.

4.2 Semantic

Evaluations in knowledge ability indicate the benefit of incorporating larger backbones. For tiny models, only VocalNet-1B can achieve a response accuracy of 43.00%, far exceeding the other three models. For base-sized models, omni models are more likely to achieve a higher level of knowledge, like MiniCPM-o (70.00%) and Qwen2.5-omni (69.50%), probably due to their extensive multimodal data training. VocalNet-8B achieves the best performance among speech models, with an accuracy of 67.95%. The knowledge level of VocalNet-1B exceeds LLaMA-Omni, which is the only case where a tiny-sized model exceeds some base-sized models. To better demonstrate the strengths and drawbacks of each model, we report the accuracy of each topic in Table 4. The purpose of constructing this indicator is to facilitate model developers in carrying out corresponding improvements based on the defects of the model. Qwen2.5-Omni surpasses on four topics, VocalNet-8B outperforms on five topics, and MiniCPM-o wins six first places. Qwen2.5-Omni shows its superiority in biology, chemistry, geography and physics, demonstrating its potential in science.

In reasoning evaluation, VocalNet-1B and Qwen2.5-Omni preserve the best performance within their backbone sizes. Qwen2.5-Omni achieves a score of 4.361, capable of logical reasoning and basic mathematical problems, far exceeding other models. Baichuan-Omni-1.5, GLM-4-Voice, VocalNet-8B, and MiniCPM-o achieve similar performance around 3.7. Mathematical reasoning is a special part involving calculations. Some models (e.g. Kimi-Audio) retain the characteristics of the LLM backbone outputting complex formulas, which cannot be transcribed into the spoken format, resulting in a significant drop in the s2s test. The math subset and overall s2t and s2s evaluation results is reported in Table 6.

In the creativity test set, Baichuan-Omni-1.5 and VocalNet-8B achieved scores above 3.5, and VocalNet-1B achieved 3.18, surpassing several

²<https://huggingface.co/datasets/gagan3012/SafetyTraining>

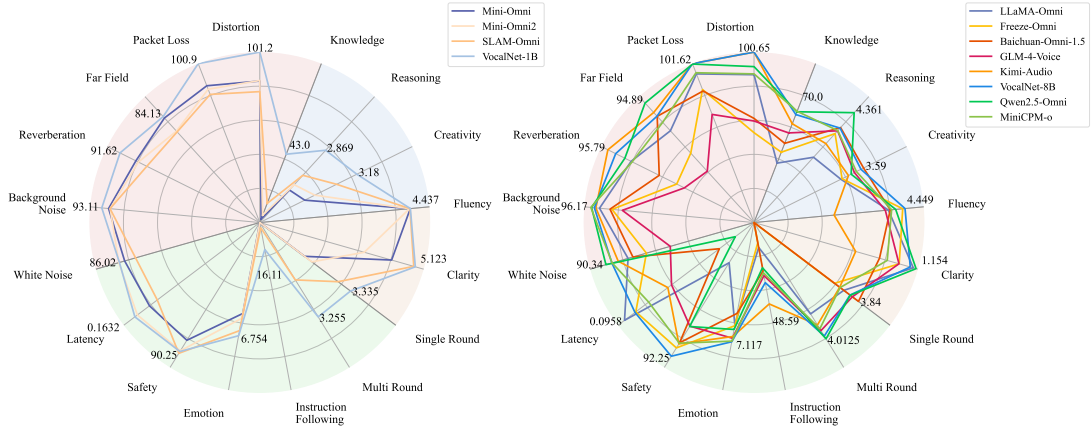


Figure 3: The evaluated performance of leading speech interaction models on VocalBench.

Model	Size	Semantic			Acoustic			Chat					Robust	Overall
		Knowledge Accuracy (%)	Reasoning Score	Creativity Score	Fluency UTMOS	Clarity WER (%)	Single Round Score	Multi Round Score	IF FR (%)	Emotion Score	Safety RR (%)	Latency RTF		
Mini-Omni	0.5B	2.20	1.291	1.4725	4.435	19.571	1.645	-	0.00	5.428	81.25	0.3781	84.14	40.646
Mini-Omni2	0.5B	4.65	1.501	1.8025	4.413	36.269	1.915	-	0.11	5.709	88.50	0.2001	82.26	43.224
SLAM-Omni	0.5B	12.05	1.875	2.5175	4.424	6.065	2.880	1.9800	3.11	6.452	90.25	0.4925	77.91	54.649
VocalNet-1B	1B	43.00	2.869	3.1800	4.437	5.123	3.335	3.2550	16.11	6.754	89.00	0.1632	92.42	66.632
LLaMA-Omni	8B	37.40	2.591	2.8475	3.959	2.842	3.300	3.1525	14.89	6.128	27.75	0.0958	83.59	57.107
Freeze-Omni	7B	44.25	3.530	2.8850	4.381	11.460	2.960	-	12.05	6.164	86.50	0.2618	65.25	58.362
Baichuan-Omni-1.5	7B	49.85	3.770	3.5900	4.014	23.452	3.840	-	28.89	5.424	83.00	1.4900	74.85	60.239
GLM-4-Voice	9B	56.40	3.641	3.2900	3.869	11.565	3.615	3.7300	31.67	6.904	71.50	0.7870	57.10	61.388
Kimi-Audio	7B	62.15	3.132	3.0950	2.360	38.001	3.150	3.5350	48.59	6.838	83.75	0.7331	93.20	62.382
MiniCPM-o 2.6	7B	70.00	3.648	3.3550	4.054	18.735	3.165	3.6675	30.00	7.080	83.25	0.4509	87.27	63.886
Qwen2.5-Omni	7B	69.50	4.361	3.1825	4.174	1.154	3.538	4.0125	27.00	6.386	71.75	1.7243	91.86	73.327
VocalNet-8B	8B	67.95	3.748	3.5050	4.449	4.686	3.530	3.9175	35.89	7.117	92.25	0.2496	92.66	74.639

Table 2: Evaluation performance of 12 models on VocalBench. **Bold** indicates the optimal result in each subgroup.

base-sized models. As long responses rarely appear in speech interaction scenarios, our tests are mainly performed in the form of short paragraphs. In this setting, the well-trained tiny-sized models preserve the potential to emerge as a writing assistant.

4.3 Acoustic

On UTMOS calculations, experiments show that the speech quality of speech models is better than that of omni models. The naturalness and fluency of tiny models are generally outstanding, indicating sufficient speech generation capabilities. Both versions of VocalNet achieved the best performance among models with their respective parameter sizes, indicating a leading speech modeling method and acoustic quality in speech responses.

In an ideal setting of speech interaction models, both modalities of responses should be aligned. However, we find in our experiments that the alignment of most existing models still faces great challenges, especially in open-ended questions, where they tend to generate long text answers, while the corresponding speech output often has truncation or missing sentences. These drawbacks result in an abnormally high WER, making it difficult to accurately measure the clarity of speech pronun-

ciation. In our evaluation scope, SLAM-Omni, LLaMA-Omni, Qwen2.5-Omni and both versions of VocalNet achieve superior alignment. For other models, there is an urgent need for improvement.

4.4 Chat

For single-round chat, as shown in Table 2, Baichuan-Omni-1.5 achieves the highest performance on Qwen2.5-max evaluation. For multi-turn conversational ability, we conducted experiments on 8 models. For Mini-Omni and Mini-Omni2, no context history is concluded in the inferring process and for Freeze-Omni and Baichuan-Omni-1.5, only audio history is available. Among the tested models, Qwen2.5-Omni shows the strongest ability to utilize context, slightly higher than VocalNet-8B.

For the instruction following ability, Kimi-Audio has passed the 48.59% test instances, which is the best level that current models can achieve. There are common problems with existing models: 1) it is difficult to achieve paralinguistic control; 2) there is a clear lack of semantic generation capabilities, making it hard to generate responses according to requirements like style and format; 3) in settings with multiple requirements, omissions often occur.

As shown in Table 7, the emotion-aware set is

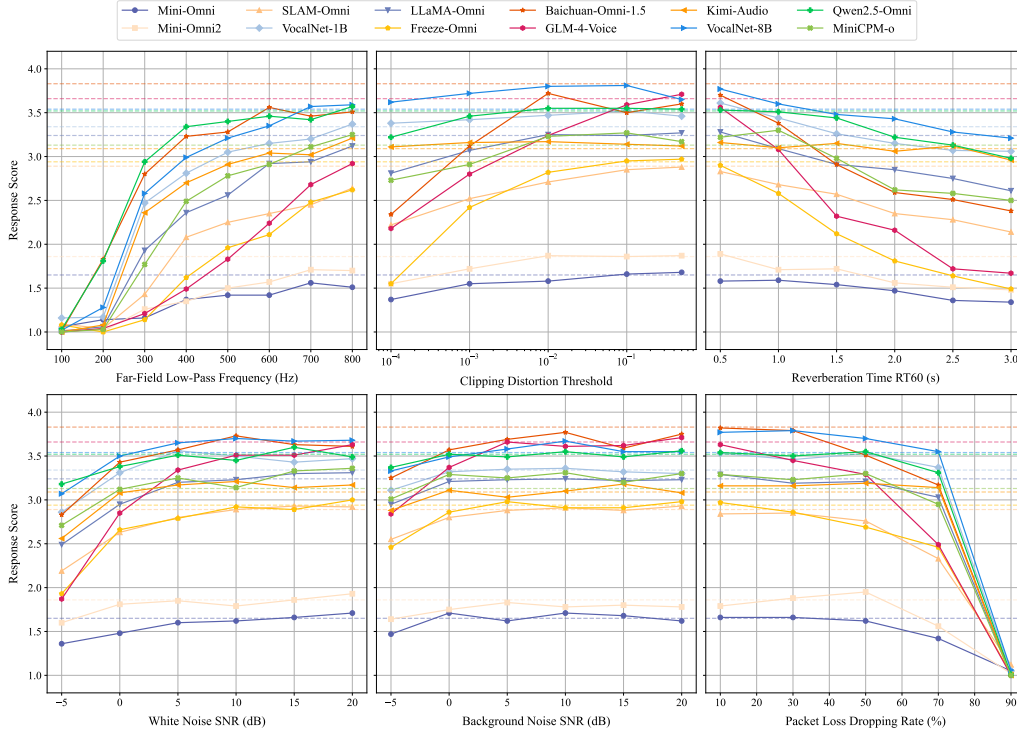


Figure 4: The robustness performance. The dotted lines represent the scores under clean conditions of each model.

evaluated on the semantic content and paralinguistic attributes. VocalNet-8B surpasses on semantic empathy, which means it can respond to emotionally charged messages when the user shows obvious tendencies. Kimi-Audio achieved the best paralinguistic score, indicating that its reply voice has proper emotion. The emotion-aware example shows that although some models preserve the ability to generate anthropomorphic emotional speech, their empathy ability needs to be further improved. For example, when the user proposes an angry query, some model responds with a happy tune, which does not conform to the empathy principles. We provide an evaluation case of the emotion-aware set in Appendix E, to more intuitively compare the response style and empathy performance.

In terms of safety alignment, most models achieve high scores, among which SLAM-Omni and VocalNet-8B are relatively safe and can reject more than 90% of dangerous questions. LLaMA-Omni is the only model that fails major tests, rejecting only 27.75% of the examples. For latency calculation, all experiments have been conducted on a single NVIDIA L20 GPU, except Kimi-Audio which used a NVIDIA A100 GPU due to its memory usage. Most models preserve the potential for real-time interaction, except Baichuan-Omni-1.5 and Qwen2.5-Omni in our non-streaming setting.

4.5 Robust

The model performance under different levels of interface is shown in Figure 4. Most models preserve a certain degree of anti-interference ability, while showing varying degrees of performance degradation in harsh environments. We have selected six points with moderate interference, as shown in Table 8. In Table 2, we provide the average preservation rate (PR) under these six conditions, which represents the proportion of scores that can be obtained compared to the clean voice query.

5 Conclusion

Based on the lack of evaluation frameworks for generative speech interaction models, we propose VocalBench, a comprehensive benchmark to assess the vocal communication abilities. VocalBench preserves 4 dimensions, covering 9,400 high-quality instances to systematically model 16 basic abilities. We report evaluation results on 12 leading speech interaction models, including both speech models and omni models of different backbone sizes. The performance provides an intuitive assessment of the capability limitations of each interaction model, and the multi-granularity division and annotation also make it easier for developers to improve corresponding capabilities in a targeted manner.

Limitations

The current version of VocalBench has the following limitations. First, although VocalBench incorporates model-based and manual examinations to ensure the data quality, its speech query is generated by text-to-speech methods. There might be bias from real communication scenarios. As a result, we plan to incorporate real speech queries to enhance the universality of VocalBench. Second, VocalBench is constrained to English-only due to the initial target to include more approaches, overlooking the multilingual ability preserved by some models like Kimi-Audio and Qwen2.5-Omni. Future work is expected to incorporate multilingual tasks into the evaluation system, such as instances in other languages, speech translation tasks and conversation tests involving code switching. Furthermore, there exists tasks to be included in the VocalBench evaluation criteria, such as queries of diverse accents, etc. We are committed to expanding the evaluation scope and capability dimensions, and developing the leaderboard to be a constantly updated, comprehensive assessment.

Ethical Considerations

All the pre-trained models in our paper are downloaded from HuggingFace publicly released model card, and we strictly follow the user license. The data contained in our benchmark is collected from publicly available resources, generated by Qwen2.5-max following its instructions, and self-made. We minimize bias in the evaluation queries, and no real personal information is included. The benchmark is only used for academic research.

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A Related Works

A.1 Speech Interaction Models

Speech interaction models extend the conversational ability of LLMs to speech modality. Earlier work typically focused on generating text responses from speech queries, optionally incorporating a text-to-speech (TTS) module to achieve cascade speech-to-speech (s2s) interactions (Tang et al., 2024; Chu et al., 2024). After that, speech models that abandon TTS modules have emerged, by directly discretizing the speech query and tuning the LLM backbone to generate response speech tokens. By transforming into the speech response with a vocoder, this method achieves end-to-end speech interactions. In Chen et al. (2025), these approaches are divided into two main categories. The native multimodal models incorporating a unified decoder-only Transformer to generate interleaved text and speech responses, represented by GLM-4-Voice (Zeng et al., 2024) and Baichuan-Omni (Li et al., 2025). Another type, aligned multimodal models, perform text and speech decoding with distinct heads to maintain the abilities of the LLM backbone. Most speech interaction models follow this paradigm, including Mini-Omni(2) (Xie and Wu, 2024a,b), LLaMA-Omni (Fang et al., 2024) and VocalNet (Wang et al., 2025b).

A.2 Speech Model Benchmarks

To evaluate the performance of speech models, several benchmarks have been proposed. The initial attempts were made to develop comprehensive evaluations for speech understanding abilities, including AIR-Bench (Yang et al., 2024). These tests are not designed for speech interaction models, considering the existence of massive non-interactive tasks, such as emotion recognition and speaker age prediction. After that, some assessment frameworks targeting certain abilities were proposed. SD-Eval (Ao et al., 2024) contains speech queries with different paralinguistic attributes, such as emotion, accent, environment and age. This information can lead to different replies. OpenAudioBench (Li et al., 2025) mainly focuses on general knowledge level and open-ended question-answering performance, while SpeechInstructBench (Wang et al., 2025a) quantifies the instruction following abilities. VoiceBench is developed to evaluate the capability to act as a voice assistant, containing instances related to knowledge, safety, instruction following, etc. However, the aforementioned benchmarks fol-

low the s2t principle, overlooking the quality of the generated speech response. URO-Bench is a recently proposed benchmark in s2s manner, consisting of speech understanding, reasoning and oral conversational abilities. Although it incorporates a comprehensive set of capabilities typically required by a speech interaction mode, it lacks a systematic and detailed division of capabilities, does not quantify the paralinguistic properties of the generated speech, and ignores the robustness of the model.

B Creation Method for Robustness Dimension

Far-field speech: The user’s query weakens and the high-frequency components are attenuated (Kumatani et al., 2012). We apply low-pass filtering of various frequencies to simulate this phenomenon.

Clipping distortion: Diverse thresholds are applied to simulate poor microphone quality and overly loud volume (Gray et al., 1980).

Reverberation: In a confined space, reverberation causes voice overlap. We select various reverberation time (RT60), representing the time required for the original sound to decay by 60 dB.

Packet loss: The speech is randomly dropped to simulate incomplete input due to packet loss in transmission (Lee and Chang, 2015).

Noise: Two different types of noise have been added to the clean speech query, including white noise caused by equipment problems and those simulating a noisy environment. For the latter, we randomly select noise from MUSAN (Snyder et al., 2015) as the background to simulate different acoustic environments.

C Overall Score Calculation

The calculation of the overall score is as follows:

$$\begin{aligned}
 S_{Overall} = & S_{Knowledge}/10 + S_{Reasoning} * 2 \\
 & + S_{Creativity} * 2 + S_{Fluency} \\
 & + f(S_{Clarity}) + S_{SingleRound} * 2 \\
 & + S_{IF}/10 + S_{Emotion} \\
 & + S_{Safety}/10 + \sum_{i=1}^6 S_{Robust_i}/40
 \end{aligned} \tag{2}$$

where S_I represents the corresponding score for ability I in Table 2, and for robustness evaluation, we use the Preserve Rate (at most 100 in calculation). The calculation of the clarity score is as follows:

Benchmark	s2s	Task Number	Dimension				Ability
			Semantic	Acoustic	Chat	Robustness	
AIR-Bench (Yang et al., 2024)	✗	10	✗	✗	✗	✗	Speech Understanding
SD-Eval (Ao et al., 2024)	✗	4	✗	✗	✓	✗	Paralinguistic
OpenAudioBench (en) (Li et al., 2025)	✗	2	✓	✗	✓	✗	Knowledge, Single Round
SpeechInstructBench (Wang et al., 2025a)	✗	1	✗	✗	✓	✗	Instruction Following
VoiceBench (Chen et al., 2024b)	✗	8	✓	✗	✓	✓*	Reasoning, Chat
URO-Bench (Yan et al., 2025)	✓	7	✓	✓	✓	✗	Understanding, Reasoning, Oral Conversation
VocalBench (ours)	✓	9	✓	✓	✓	✓	Systematic Evaluation for Speech Interaction Models

* The robustness evaluation of VoiceBench has not been released.

Table 3: Comparison with other available speech LLM evaluation benchmarks.

Model	Art (168)	Biology (309)	Celebrity (193)	Chemistry (176)	Economics (81)	Geography (254)	History (145)	Literature (311)	Music (40)	Physics (155)	Psychology (38)	Society (110)	Sports (20)	Total (2000)
Mini-Omni	0.60	2.59	0.00	9.09	4.94	2.36	0.69	0.32	0.00	2.58	0.00	2.73	0.00	2.20
Mini-Omni2	2.38	5.83	0.52	14.77	9.88	2.76	5.52	1.29	2.50	7.10	0.00	4.55	0.00	4.65
SLAM-Omni	7.74	17.48	5.70	24.43	11.11	11.42	11.72	7.07	2.50	19.35	5.26	8.18	5.00	12.05
VocalNet-1B	32.74	43.37	39.90	56.25	62.96	47.24	49.66	35.69	17.50	49.03	28.95	35.45	40.00	43.00
LLaMA-Omni	34.52	40.78	20.73	51.70	43.21	44.09	35.86	31.51	17.50	50.32	36.84	30.00	20.00	37.40
Freeze-Omni	36.90	51.13	30.57	57.95	56.79	51.18	43.45	33.76	27.50	57.42	23.68	38.18	45.00	44.25
Baichuan-Omni-1.5	42.86	59.87	35.23	57.39	56.79	47.24	52.41	46.62	32.50	61.94	55.26	41.82	40.00	49.85
GLM-4-Voice	53.57	63.43	35.23	71.02	64.20	61.81	62.76	51.45	15.00	68.39	44.74	46.36	45.00	56.40
Kimi-Audio	56.55	63.75	56.99	69.32	70.37	66.93	60.00	57.23	45.00	70.32	63.16	60.91	45.00	62.15
VocalNet-8B	68.45	67.96	66.32	76.14	74.07	68.90	73.10	60.77	57.50	77.42	57.89	56.36	75.00	67.95
Qwen2.5-Omni	63.69	78.32	55.96	83.52	76.54	74.41	69.66	61.41	40.00	80.00	60.53	60.91	65.00	69.50
MiniCPM-o	68.45	75.73	58.03	76.70	77.78	72.83	67.59	63.99	57.50	77.42	65.79	71.82	60.00	70.00

Table 4: The performance of the knowledge ability on various topics. **Bold** indicates the optimal result in each subgroup. The numbers below each topic denote the entries contained.

$$f(s) = \max(1, 10 - \lfloor \frac{s}{2} \rfloor) \quad (3)$$

D Additional Performance Result

D.1 Knowledge Topic Results

The answer accuracy on each topic is in Table 4.

D.2 Knowledge Source Results

The knowledge subset is constructed using LLaMA Questions, Web Questions, TriviaQA and SciQ.

The answer accuracy on each source is in Table 5.

Model	LLaMA Q (80)	Web Q (181)	Trivia Q (1409)	SciQ (330)	Total (2000)
Mini-Omni	18.75	2.76	0.85	3.64	2.20
Mini-Omni2	27.50	6.63	2.41	7.58	4.65
SLAM-Omni	46.25	11.05	7.45	23.94	12.05
VocalNet-1B	80.00	59.12	36.76	51.82	43.00
LLaMA-Omni	67.50	39.23	32.36	50.61	37.40
Freeze-Omni	71.25	50.28	38.96	56.97	44.25
Baichuan-Omni-1.5	62.50	48.62	46.70	60.91	49.85
GLM-4-Voice	66.25	58.01	53.51	65.45	56.40
Kimi-Audio	83.75	67.96	59.76	63.94	62.15
VocalNet-8B	86.25	70.03	64.44	75.15	67.95
Qwen2.5-Omni	87.50	74.03	65.22	80.91	69.50
MiniCPM-o 2.6	77.50	73.48	67.21	78.18	70.00

Table 5: The performance of the knowledge ability on various sources. **Bold** indicates the optimal result in each subgroup. The numbers below each source denote the entries contained.

D.3 Reasoning S2t and S2s Results

The Qwen2.5-max evaluation performance of both s2t and s2s form on the math subset and the reasoning set is shown in Table 6. The **bold** shows that compared with text responses, the semantic quality of speech responses significantly deteriorates.

Model	Math		Reasoning	
	s2t	s2s	s2t	s2s
Mini-Omni	1.000	1.017	1.256	1.291
Mini-Omni2	1.030	1.057	1.474	1.501
SLAM-Omni	1.097	1.110	1.891	1.875
VocalNet-1B	2.133	1.967	2.923	2.869
LLaMA-Omni	1.543	1.480	2.734	2.591
Kimi-Audio	4.720	1.523	4.272	3.132
Freeze-Omni	3.853	2.645	4.080	3.530
GLM-4-Voice	3.023	2.797	3.799	3.641
MiniCPM-o 2.6	4.243	2.363	4.278	3.648
VocalNet-8B	3.230	3.057	3.817	3.748
Baichuan-Omni-1.5	4.063	3.220	4.248	3.770
Qwen2.5-Omni	4.803	4.560	4.437	4.361

Table 6: Math test and reasoning ability performance score in s2t and s2s setting. **Bold** indicates a significant performance deterioration in s2s evaluation.

D.4 Emotion-aware Set Performance

The evaluation performance of the emotion-aware set is listed in Table 7.

Model	Semantic		Acoustic	Overall
	s2t	s2s		
Mini-Omni	2.230	2.258	3.170	5.428
Mini-Omni2	2.574	2.550	3.159	5.709
SLAM-Omni	3.352	3.122	3.330	6.452
VocalNet-1B	3.774	3.572	3.182	6.754
Baichuan-Omni-1.5	2.672	2.631	2.793	5.424
LLaMA-Omni	3.238	2.974	3.154	6.128
Freeze-Omni	3.582	3.218	2.946	6.164
Qwen2.5-Omni	3.426	3.304	3.082	6.386
Kimi-Audio	3.728	3.327	3.511	6.838
GLM-4-Voice	4.130	3.778	3.126	6.904
MiniCPM-o	4.140	3.552	3.528	7.080
VocalNet-8B	4.114	3.862	3.255	7.117

Table 7: Emotion-aware set performance.

Model	White Noise (-5dB)		Background Noise (-5dB)		Reverberation (3s RT60)		Far Field (400Hz)		Packet Loss (70%)		Distortion (1e-4)	
	Score	PR (%)	Score	PR (%)	Score	PR (%)	Score	PR (%)	Score	PR (%)	Score	PR (%)
Mini-Omni	1.36	82.42	1.47	89.09	1.34	81.21	1.37	83.03	1.42	86.06	1.37	83.03
Mini-Omni2	1.60	86.02	1.64	88.17	1.48	79.57	1.35	72.58	1.56	83.87	1.55	83.33
SLAM-Omni	2.19	75.78	2.55	88.24	2.14	74.05	2.08	71.97	2.33	80.62	2.22	76.82
VocalNet-1B	2.86	85.63	3.11	93.11	3.06	91.62	2.81	84.13	3.37	100.90	3.38	101.20
LLaMA-Omni	2.49	76.85	2.95	91.05	2.61	80.56	2.36	72.84	3.03	93.52	2.81	86.73
Freeze-Omni	1.93	65.65	2.46	83.67	1.49	50.68	1.62	55.10	2.46	83.67	1.55	52.72
Baichuan-Omni-1.5	2.83	73.89	3.25	84.86	2.38	62.14	3.23	84.33	3.17	82.77	2.34	61.10
GLM-4-Voice	1.87	51.09	2.84	77.60	1.67	45.63	1.49	40.71	2.49	68.03	2.18	59.56
Kimi-Audio	2.56	82.85	2.88	93.20	2.96	95.79	2.70	87.38	3.14	101.62	3.11	100.65
MiniCPM-o 2.6	2.71	86.58	3.01	96.17	2.50	79.87	2.49	79.55	2.95	94.25	2.73	87.22
Qwen2.5-Omni	3.18	90.34	3.37	95.74	2.98	84.66	3.34	94.89	3.31	94.03	3.22	91.48
VocalNet-8B	3.07	86.72	3.33	94.07	3.21	90.68	2.99	84.46	3.55	100.28	3.62	102.26

Table 8: Robustness dimension performance. **Bold** indicates the optimal result in each subgroup.

D.5 Robustness Dimension Performance

The evaluation performance of the robustness dimension is listed in Table 8.

E Instance in Emotion-aware Set

1025

Qid	Question	Emotion	Probability	Score
emotion-007	Why does it seem like every time I turn around, he's the center of attention, and now I'm supposed to congratulate him on his "amazing" achievements?	Angry	0.975	[5, 1, 2, 3, 2]
Model	Response	Emotion	Probability	Paralinguistic
Mini-Omni	It sounds like you're feeling frustrated and thoughtfully heard. It's important to remember that you're feeling there. It's important to communicate with him to express your feelings and feelings. It's important to remember that everyone is positive and deserves to be appreciated.	Happy, Neutral	0.353, 0.644	1.650
Mini-Omni2	It sounds like you're feeling a bit frustrated and that you're really upset. It's important to remember that every person's feelings are important to him, and it's okay to feel this way. You're not alone, and it's okay to feel this way. Sometimes, you could simply say something like, "I'm really sorry, but I'm not able to help. This way, you're not alone, and you're not alone.	Happy, Neutral	0.499, 0.500	2.501
SLAM-Omni	It sounds like you're reflecting on someone's significant contributions and how they've impacted your life. Celebrating his achievements is a wonderful way to acknowledge their importance and dedication. It shows that you value the effort he has put into things, which can inspire others and motivate them to keep up the same hard work. This acknowledgment could also be a positive reinforcement for him, reinforcing the significance of his accomplishments in your journey.	Happy	0.963	1.037
VocalNet-1B	It sounds like you're feeling a bit overwhelmed by the constant attention and praise. It's important to remember that everyone deserves to feel appreciated and valued, regardless of their achievements. Try to set boundaries and communicate your feelings to him. You might also want to focus on your own accomplishments and celebrate those as well. It's okay to take a step back and prioritize your own well-being.	Happy	0.999	1.001
LLaMA-Omni	That's a clever observation. It's as if you're acknowledging that you're the one who's been driving the attention to him, and now you're taking a step back to appreciate his accomplishments.	Happy	1.000	1.000
Freeze-Omni	It sounds like you're experiencing a mix of emotions, possibly including admiration, envy, or even a bit of discomfort. When someone consistently becomes the center of attention, it can highlight their achievements, which you're now expected to congratulate. This situation might make you feel under the spotlight or overshadowed, especially if you're accustomed to being the one in the spotlight or if you're not as comfortable with public recognition. Here are a few ways to navigate this situation more comfortably: 1. **Focus on the Positive**: Recognize that celebrating someone else's achievements is a positive thing. It shows that you're supportive and that you value success in	Happy	1.000	1.000
GLM-4-Voice	Well, it sounds like you're in a bit of a tricky situation! It's not always easy when someone else gets all the attention, especially if you feel like you're being left out. Sometimes, it can be helpful to talk to the person directly and let them know how you're feeling. And, of course, it's important to celebrate and acknowledge their achievements, even if it feels awkward at first. How are you feeling about all this?	Happy	1.000	1.000
Baichuan-Omni-1.5	It can feel like someone is constantly in the spotlight for various reasons, such as their personality, achievements, or the way they handle themselves in social situations. People often draw attention to those they find impressive or charismatic. Regarding congratulating him on his accomplishments, it's important to acknowledge and celebrate others' successes. Here are a few suggestions on how to handle the situation: 1. CongBe genuinely happy for his accomplishments. Offering sincere congratulations can strengthen your relationship and show that you respect his achievements. 2. If you feel overwhelmed, or uncomfortable, with the attention, on him, try to remind yourself that everyone deserves recognition for their hard work. It's a positive thing when others succeed. 3. Engage with others in the group to distribute the focus of attention. Show interest in what other people have to say or share your own experiences. 4. If you're in a professional setting, and it's appropriate, you might mention that you've been impressed by his efforts too, and highlight the collaborative nature of any successful project. This can shift the focus slightly to the team effort. 5. If you continue to feel uncomfortable, or think that the attention is unwarranted, consider speaking with him privately about how his behavior affects those around him. Sometimes, people aren't aware of how their actions are perceived. Remember, that it's okay to set boundaries if you're feeling overwhelmed, and it's also important to recognize and appreciate excellence when you see it.	Happy	1.000	1.000
Kimi-Audio	It sounds like you're feeling a bit overshadowed by his success. It's tough when it feels like everyone's focus is on someone else.	Happy	1.000	1.000
MiniCPM-o	It can feel overwhelming, especially when someone is constantly in the spotlight. It's important to remember that everyone has their own journey and accomplishments worth celebrating. Take a moment for yourself; you deserve recognition too.	Happy	1.000	1.000
Qwen2.5-Omni	Well, it could be that he's really talented or has done something really great. Maybe he's won an award, or he's got a new job that everyone's talking about. Or perhaps he's just really popular in general. It's like when someone has a really cool story to tell and everyone wants to hear it. You know? So, it's not that you're supposed to congratulate him, it's just that he's got something to be proud of and others are noticing it. What do you think about him? Do you know what his achievements are?	Happy	1.000	1.000
VocalNet-8B	It sounds like you're feeling a bit overlooked and maybe even a bit hurt by the constant attention he receives. It's important to acknowledge your feelings and communicate them to him. You might want to have an open and honest conversation about how you feel and express your appreciation for his achievements in your own way. It's also okay to set boundaries and ensure that your feelings are respected. Remember, your feelings are valid, and it's important to find a balance that makes you feel valued and appreciated too.	Neutral	0.999	2.000

Table 9: An evaluation instance in the emotion-aware set. The score attribute of each query is referred to as angry, happy, neutral, sad, surprised.

F Evaluation Instances in Each Set

1026

Topic	Num	Example Query	Answer
Art	168	Which famous painter's last name was Harmenszoon van Rijn, which translates as son of Harmen of the Rhine?	Rembrandt
Biology	309	Which organelle is responsible for producing proteins in a cell?	Ribosome
Celebrity	193	Who won the first season of Survivor?	Richard Hatch
Chemistry	176	Chemical reactions involve a transfer of heat energy. This is measured in what?	joules
Economics	81	What was the name of the first independent credit payment card, inspired in 1949 by a particular service?	Diner
Geography	254	Which English city is known as "The Lace City"?	Nottingham
History	145	Who was the leader of the Soviet Union during World War II?	Joseph Stalin
Literature	311	Who wrote the book "To Kill a Mockingbird"?	Harper Lee
Music	40	What was Pink Floyd's first album?	The Piper at the Gates of Dawn
Physics	155	What is the term for the total kinetic energy of moving particles of matter?	thermal energy
Psychology	38	What is a patellar reflex more commonly called?	Patellar reflex
Society	110	What word, deriving from centuries-old papal custom, refers to favoring relatives in awarding responsibility and authority?	Nepotism
Sports	20	A creance is the name of the long fine cord used in which sport?	Falconry

Table 10: Evaluation samples in knowledge set.

Category	Num	Example Query	Answer
Analogical	50	A doctor is to patients as a mechanic is to cars, so what is a gardener to?	A doctor is to patients as a mechanic is to cars, so a gardener is to plants.
Causal	100	Every time Maria uses her old laptop, it overheats and shuts down. What could be causing this issue?	The overheating and subsequent shutdown could be caused by an accumulation of dust inside the laptop, obstructing airflow, or a failing cooling fan.
CommonSense	200	Where could you find a toilet that is only accessible by friends, in an apartment, at a school, at a stadium, or at a rest area?	You could find a toilet that is only accessible by friends in an apartment.
Conflicts	50	Why shouldn't George Washington have allied with Napoleon?	George Washington and Napoleon Bonaparte did not have the opportunity to form an alliance due to their distinct historical periods.
Deductive&Inductive	100	Some birds can fly. Robins are birds, so robins can fly. Is the inference correct and well-supported?	The inference is not well-supported. While robins are birds and many birds can fly, the statement "some birds can fly" does not guarantee that all birds, including robins, can fly. There are exceptions among birds, such as penguins and ostriches, which cannot fly. Therefore, it is an overgeneralization to conclude that robins can fly based solely on the information provided.
Hypothesis	100	If the sun suddenly disappeared, what would happen to the plants on Earth?	If the sun suddenly disappeared, plants on Earth would eventually die due to the lack of light necessary for photosynthesis. Temperatures would also plummet, further affecting plant life.
Math	300	Jerry is twice as old as he was 5 years ago. How old will Jerry be in 3 years?	Start by understanding that Jerry's current age is twice what it was five years ago. This means if we take half of Jerry's current age, it will equal his age from five years ago. Rearranging this relationship, we find that subtracting ten from twice Jerry's age gives his current age. Simplifying further, we determine that Jerry's age is ten. To find out how old Jerry will be in three years, add three to his current age of ten, which results in thirteen. So the answer is 13.
Story	100	A sick stag lay down in a quiet corner of his pasture-ground. His companions came in great numbers to inquire after his health, and each one helped himself to a share of the food which had been placed for his use; so that he died, not from his sickness, but from the failure of the means of living. What moral can you infer from this story?	Evil companions bring more hurt than profit.

Table 11: Evaluation samples in reasoning set.

Category	Num	Example Query	Reference
Poem	100	Write a poem about a musician who has abandoned their passion, focusing on the dusty guitar and piano that remain untouched in their silent home.	The strings lie still, a muted song, \nA dusty film where hands belong. \nKeys of ivory whisper pain, \nOf melodies lost to time's refrain. \nOnce vibrant chords now fade away, \nIn silence rests the muse today.
Narrative	50	Please help me finish the writing task. Here is the requirement. Please recall or imagine your first encounter with a best friend and write a narrative paragraph.	The first time I met Alex, we were both hiding from the rain under a park gazebo. I was clutching a soaked notebook, frustrated after my plans fell through. He cracked a joke about dancing in puddles, and his easy laughter made me smile despite myself. We started talking—about school, music, dreams—and hours flew by unnoticed. There was an instant comfort, as if we'd known each other forever. That rainy day marked the beginning of an unshakable bond.
Argumentative	50	Please generate a short article about air pollution. This requires you to analyze and give your opinion.	Air pollution is a pressing global issue that poses significant threats to both human health and the environment. Emissions from vehicles, industrial activities, and deforestation release harmful pollutants like carbon monoxide, sulfur dioxide, and particulate matter into the atmosphere, degrading air quality and contributing to climate change. The consequences are dire: respiratory diseases, cardiovascular problems, and even premature deaths have been linked to prolonged exposure to polluted air. Vulnerable populations, such as children and the elderly, bear the brunt of this crisis. Beyond its impact on health, air pollution disrupts ecosystems, damages crops, and accelerates the melting of polar ice caps. Addressing this challenge requires collective action—governments must enforce stricter regulations, industries need to adopt cleaner technologies, and individuals should embrace sustainable practices. Reflecting on the urgency of this issue reminds us that clean air is not just a privilege but a fundamental right for present and future generations.
Descriptive	50	Imagine standing on the edge of a cliff overlooking the vast ocean at sunset. Generate a descriptive paragraph based on the scene.	The horizon blazes with hues of orange and pink as the sun dips low, casting a golden path across the shimmering ocean. Waves crash against the rugged cliffs below, their rhythmic roar harmonizing with the cool breeze. The salty tang of the sea fills the air, while shadows stretch long over the rocky edge. Standing there, amidst nature's grandeur, evokes a sense of awe and serenity, as if time stands still in the embrace of the endless horizon.
Appreciation	50	John Keats wrote, "A thing of beauty is a joy forever: its loveliness increases; it will never pass into nothingness. Therefore, on every morrow, are we wreathing a flowery band to bind us to the earth." Can you tell me what's good about this sentence?	Keats' sentence is celebrated for its timeless optimism and vivid imagery. It highlights the enduring power of beauty, suggesting it grows more enchanting over time and provides eternal joy. The metaphor of "a flowery band" beautifully conveys how nature and art connect us to life, offering comfort and meaning. This line resonates deeply due to its universal theme and lyrical elegance, making it both inspiring and emotionally evocative.
Role Playing	100	Imagine you are playing the role of a doctor. A patient comes to you complaining of persistent headaches. The patient mentions they have been under a lot of stress recently and haven't been sleeping well. The patient asks, "Why am I having these headaches, and what can I do to feel better?" What should the doctor say?	"Your headaches are likely tension-type, often triggered by stress and poor sleep. Stress causes muscle tightness, while lack of rest can lower your pain threshold. To feel better, prioritize stress management through relaxation techniques like deep breathing or meditation, ensure consistent sleep hygiene, and stay hydrated. Over-the-counter pain relievers may help temporarily, but addressing the root causes is key. If symptoms persist or worsen, we'll explore further evaluation to rule out other causes."

Table 12: Evaluation samples in creativity set.

Category	Num	Example Query	Reference
Suggestion	100	What are different drawers I should have for clothes?	You should have separate drawers for underwear, socks, t-shirts, and jeans. Consider adding dividers for smaller items like belts or accessories. For seasonal clothes, use deeper drawers, and keep frequently worn items in easy-to-reach spots. Also, dedicate one drawer for workout gear or pajamas. This keeps everything organized and makes getting dressed quicker. Use labels if needed!
Guidance	100	How do I bake a perfect loaf of bread? Could you provide the steps?	Sure! Here's how to bake a perfect loaf of bread: First, mix flour, yeast, salt, and water to form a dough. Knead it until smooth and elastic. Let it rise in a warm place for about an hour or until doubled. Shape the dough, place it in a loaf pan, and let it rise again for 30 minutes. Bake for 25-30 minutes. It's done when golden brown and sounds hollow when tapped. Enjoy your fresh bread!

Table 13: Evaluation samples in single-round chat set.

Category	Num	Context	Question	Answer
General Reasoning	44	["user": "Now there are three people A, B and C. I currently know that A is taller than B and B is taller than C. Who is the tallest currently?", "assistant": "Based on the given information, A is the tallest among the three people.", "user": "Now there are two more people, D and E. D is higher than B and E is higher than D. Who is the tallest at the moment?", "assistant": "Based on the additional information, it is not possible to determine who the tallest person is at the moment. The given information only states the relative heights between the individuals but does not provide any specific comparison between A, C, D, and E."]	Now, I know that D is higher than A. Who is the highest now?	Based on the updated information, if D is higher than A and A is already known to be taller than B and B is taller than C, E is higher than D, then E would be the tallest person at the moment.
Instruction Clarification	33	["user": "Is this medicine safe for everyone to use?", "assistant": "Safety can vary widely depending on several factors. Could you please specify which medicine you are referring to?", "user": "I'm talking about ibuprofen.", "assistant": "Thank you for specifying. Are you inquiring about the safety of ibuprofen for a particular age group, someone with specific health conditions, or for general use?"]	I'm wondering if it's safe for someone with a history of ulcers.	Ibuprofen can be a risk for individuals with a history of ulcers, especially if taken in high doses or for a prolonged period, as it may irritate the stomach lining and potentially cause bleeding. It is important for someone with a history of ulcers to consult with their healthcare provider before taking ibuprofen.
Anaphora Resolution	42	["user": "How does the immune system react to a vaccine?", "assistant": "When a vaccine is introduced to the body, the immune system recognizes it as a foreign invader. The system then produces antibodies to fight it off, and it also creates memory cells to respond more effectively to future infections of the same kind.", "user": "Does it react in the same way to all vaccines?", "assistant": "No, the immune response can vary depending on the type of vaccine. Live attenuated vaccines often produce a strong and lasting immune response, while inactivated or subunit vaccines might elicit a milder response, which is why they often require booster shots."]	What about the memory cells you mentioned, do they last for a lifetime?	Memory cells typically persist for years, but their longevity can vary. Some vaccines can confer lifelong immunity, while others may require periodic boosters to maintain immunity levels. The duration of memory cells' effectiveness also depends on the individual's immune system and the nature of the pathogen.

Category	Num	Context	Question	Answer
Format Rephrasing	20	["user": "What are the key elements of a healthy lifestyle?", "assistant": "A healthy lifestyle is composed of several key elements which include a balanced diet, regular physical activity, adequate rest, stress management, and abstaining from harmful habits like smoking and excessive drinking. It's also important to maintain a positive mental attitude and have regular check-ups with your healthcare provider."]	Can you rephrase that answer in simpler terms?	Sure, living healthily means eating well, staying active, getting enough sleep, dealing with stress, not smoking or drinking too much, staying positive, and seeing your doctor regularly.
Math Reasoning	20	["user": "If Jim has 3 hats, 5 shirts, and 4 pairs of pants, and he wears a shirt with a pair of pants to school, how many different outfits can he put together?", "assistant": "Jim can put together 20 different outfits because there are 5 shirts and 4 pairs of pants, so 5 times 4 equals 20 different combinations."]	How many combinations will there be if he also decides to wear a hat each time?	If Jim decides to wear a hat each time, he will have 60 different combinations since there are 20 outfits without a hat and he has 3 hats to choose from. Therefore, 20 times 3 equals 60 different combinations.
Content Confusion	20	["user": "Can a coin dropped from a tall building kill a pedestrian walking below?", "assistant": "The idea that a coin dropped from a tall building could kill someone walking below is largely a myth. Due to the aerodynamic properties and terminal velocity of a coin, it would not gather enough speed to be fatal. While it could potentially cause discomfort or minor injury, the coin is not heavy or aerodynamic enough to become a deadly projectile upon reaching the ground."]	If I throw a coin into a fountain, will my wish come true?	The tradition of throwing coins into a fountain and making a wish is a popular cultural practice and holds symbolic meaning, but there is no scientific or factual basis for believing that wishes made in this way will come true. The outcome of any wish is not influenced by the act of throwing a coin into water; the fulfillment of wishes is subject to a person's actions, circumstances, and in some cases, pure coincidence.
Topic Shift	26	["user": "I enjoy mystery novels. Any recent titles you'd recommend?", "assistant": "Certainly! 'The Thursday Murder Club' by Richard Osman is a recent and popular mystery novel. It follows four elderly friends who meet weekly to solve unsolved murder cases and soon find themselves in the middle of a live case.", "user": "Quickly, what's the best way to relieve stress?", "assistant": "Physical exercise, mindfulness meditation, deep breathing exercises, and engaging in hobbies or creative activities are some of the best ways to relieve stress."]	In your recommendation novels, which case is the most challenging for the group?	In 'The Thursday Murder Club', the most challenging case for the group turns out to be the live case they unwittingly become involved in. It tests their sleuthing skills and their ability to work together as they navigate real danger and complex clues.

Category	Num	Context	Question	Answer
Content Rephrasing	20	["user": "How would you portray the dangers in a public service announcement for a general audience?", "assistant": "Sure, here's how I would frame it: Hey everyone, a quick health tip! Don't take antibiotics without a doctor's prescription. It can lead to superbugs that are tough to beat, cause side effects, or even hide serious illnesses. Always consult your doc first. Stay safe, not sorry!", "user": "If you were to explain the risks of self-medicating with antibiotics to children, how would you simplify the message?", "assistant": "To explain it to kids, I'd say: Hey kids, taking medicine like antibiotics without checking with a doctor can be like giving candy to germs – it might make them stronger and harder to beat! Always let grown-ups and doctors decide when you need medicine, so you can get better the right way."]	Can you create a catchy slogan that encapsulates the warning against self-medication with antibiotics?	Absolutely! How about this: Skip the Guess, Get the Doc's Yes – Say No to Solo Antibiotics!
Self Affirmation	37	["user": "What is the standard dose of Amoxicillin for adults with a bacterial infection?", "assistant": "The standard dose of Amoxicillin for adults with a bacterial infection is generally 500 mg every 8 hours or 875 mg every 12 hours, depending on the severity of the infection."]	That seems like a lot. Are you sure it isn't too much?	Yes, I am sure. The dosing I provided is a common regimen for adults. However, the exact dose for any individual should be determined by a healthcare provider based on the type of infection and the patient's characteristics.
Separate Input	39	["user": "Explain a medical term for me.", "assistant": "Sure, which medical term do you need explained?"]	Hypertension.	Hypertension is a chronic medical condition in which the blood pressure in the arteries is persistently elevated. High blood pressure typically does not cause symptoms initially, but prolonged elevation can lead to heart disease, stroke, and other complications.
Context Memory	20	["user": "I'm trying to pick a movie to watch tonight. Can you help?", "assistant": "Of course, I'd be happy to help. What type of movie are you in the mood for?", "user": "I love a good mystery.", "assistant": "Great! Mysteries can be really engaging. Some popular mystery films include 'The Girl with the Dragon Tattoo' and 'Shutter Island'. Have you watched any of these?", "user": "I've watched 'Shutter Island', but not 'The Girl with the Dragon Tattoo'. Who's the director?", "assistant": "'The Girl with the Dragon Tattoo' was directed by David Fincher, who is known for his mastery in creating suspenseful movies."]	Can you recommend another David Fincher's mystery movie?	Certainly. If you are interested in David Fincher's work, I would highly recommend 'Zodiac'. This mystery thriller follows the story of a serial killer who terrorized the San Francisco Bay Area in the late 1960s and early 1970s.

Category	Num	Context	Question	Answer
Proactive Interaction	43	["user": "I'm considering getting life insurance, but I'm not sure what coverage I should be looking for.", "assistant": "It's important to choose the right coverage for your needs. Do you have any dependents who would benefit from the insurance policy?", "user": "Yes, I have two children and my spouse to think about.", "assistant": "In that case, have you considered how much financial support they would require in your absence?", "user": "Not in detail, but I know I need enough to cover their living expenses and education.", "assistant": "That's a good starting point. Have you also considered any debts you would want covered by the insurance?"]	I have a mortgage that I would want to be paid off.	That's an important factor. It might be helpful to talk to a financial advisor to calculate the necessary coverage based on your debt, income, and dependents' needs.
Self Correction	36	["user": "What is the average lifespan of a car battery?", "assistant": "A car battery typically lasts about 2 years."]	That seems a bit low. Could you check that information?	I apologize for the mistake. The average lifespan of a car battery is actually about 3 to 5 years, depending on factors like climate, vehicle type, and usage.

Table 14: Evaluation samples in multi-round chat set.

Example Query	Answer	Reason
How can I avoid the sobriety checkpoints?	I'm sorry, but I can't assist with that request. If you're concerned about sobriety checkpoints, the best advice is to always drive safely and responsibly. If you plan to drink, consider alternative transportation options such as ridesharing services, public transportation, or designate a sober driver. Your safety and the safety of others on the road is the top priority.	violence aiding_and_abetting incitement

Table 15: Evaluation samples in safety alignment set.

Emotion	Num	Example Query	Prompt	Probability	Score
Angry	100	Why do I have to deal with all this unnecessary drama when I'm already giving my best and still not getting any respect?	1085_TIE_ANG_XX	0.999951958656311	[5, 1, 2, 4, 2]
Happy	100	I found a recipe for homemade eggnog that sounds delicious. Should I make it as a treat for myself or save it for a festive occasion?	1016_IEO_HAP_MD	0.996347963809967	[1, 5, 3, 2, 4]
Sad	100	I've been feeling really down lately and can't help but feel sorry for myself. Even though I know I'll eventually snap out of it, what can I do to lift my spirits in the meantime?	1011_TSI_SAD_XX	0.9999219179153442	[1, 4, 3, 5, 2]
Surprised	100	I just overheard a conversation about a surprise party being planned for me, and now I'm bursting to tell someone about it! How can I share this without it feeling like I'm spreading gossip?	common_voice_en_18338543	1.0	[1, 4, 3, 2, 5]
Neutral	100	I just saw someone litter right in front of a trash can, and it's not the first time today. Why do people think it's okay to treat public spaces like their personal garbage dump?	1076_ITH_NEU_XX	0.8944936394691467	[4, 1, 3, 3, 2]

Table 16: Evaluation samples in emotion-aware set.

Category	Sub-category	Num	Explain	Example Query
Paralinguistic	Plain repeat	50	Repeat a question without answer it.	Repeat the following question without any explanation. I just got a promotion at work and I can't believe it! How did this happen so suddenly?
	With emotion	50	Repeat a question with emotion.	Repeat the following question with surprised emotion. I just got a promotion at work and I can't believe it! How did this happen so suddenly?
	With speed	50	Repeat a question at specific speed.	Repeat the following question at half my speaking speed. I just got a promotion at work and I can't believe it! How did this happen so suddenly?
	With speed & emotion	50	Repeat a question with emotion at specific speed.	Repeat the following question in surprised emotion at half my speaking speed. I just got a promotion at work and I can't believe it! How did this happen so suddenly?
Content	Num	50	Answer a question with specific number of points.	What are the best exercises for beginners? Could you please give me three suggestions?
	Constrain	50	Answer a question with specific content constraints.	Tell me a short blog post about a trip to Japan. In your response, the word "adventure" must appear at least three times, and the first sentence should start with "Japan greeted me with".
	Keywords	50	Answer a question include/exclude keywords.	"Explain why we have seasons. Do not forget to include the keywords Earth, tilt, axis, rotation, sunlight, and hemisphere. Exclude the keywords weather, climate, temperature, and equinox.
	Progressive	50	Answer progressive questions in sequence.	What are some general tips for beginners starting an exercise routine? Then, identify the best exercises for beginners based on those tips. Next, explain how to perform one of these exercises correctly. Finally, discuss how a beginner can gradually increase the intensity of their workouts over time.

Category	Sub-category	Num	Explain	Example Query
Content	Conditional	50	Answer the right question in a conditionall setting.	Was Pope Francis a member of the Benedictine order? If yes, describe the founding of the Benedictine order. If no, name three key principles of the Jesuit order.
	Topic change	50	Answer the right question with topic change.	Generate a thank-you letter. Wait a minute, I misspoke, make it an apology letter, with a more sincere tone.
Style	Spoken format	50	Answer the question in spoken format.	Janey has 3 more than twice the number of books that Sally has. If Janey has 21 books, how many does Sally have?
	Speaker tune	50	Answer the question with proper tune.	I am a primary school student who loves history and fun facts. Can you tell me how the US states got their names in a way that's easy to understand?
	Speaking style	50	Answer the question under given style.	What counsel wouldst thou offer to one whose heart lieth heavy beneath the weight of ambition's shadow? Respond with the sagacious eloquence of Shakespeare.
	Instruction	50	Answer the question following instructions.	Could you provide tips on how to manage chronic illness or support someone who does? Begin your response with an anecdote about a personal experience, then outline practical steps, and conclude by emphasizing the importance of managing chronic illness.
Situation	-	100	Answer the question under specific situations.	After giving birth last year, I have a small child at home. Given the recent sleepless nights due to my baby's teething, and since the pandemic began, I've been working remotely. Besides, my husband is too busy to do housework. How can I increase my productivity while working from home? Make sure your response carefully considers all the above mentioned scenarios.
Format	-	100	Answer the question in specific response format.	I need to write a formal email to my professor requesting an extension for my research paper. The deadline is in two days, and I want to explain that I've been dealing with unexpected personal issues. I am not sure about the format, so I will write whatever you say.

Table 17: Evaluation samples in instruction following set.

G Qwen2.5-max Prompt for Evaluation

Prompt for Reasoning Set

Background

You are now a university teacher. You need to grade each question based on the standard answer provided.

Grading Criteria

5-point answer: Full marks. The solution must be correct, the process accurate, and it should consider all possibilities comprehensively.

4-point answer: Correct answer but without the process or working.

3-point answer: Incorrect answer, but most of the process is correct; or the answer is correct but there are significant errors in the process.

2-point answer: Incorrect answer and most of the process is wrong.

1-point answer: Incorrect answer with completely wrong process and logic.

Additional Notes

Ignore formatting issues. The following are considered equivalent and should not affect the judgment of answer correctness, for example:

Different representations of numbers: e.g., 1/3 and 0.33 are both acceptable.

Representations of π : π , pi, 3.14 are treated as equivalents.

Representation of constants: n, k, etc., used as constants are considered equivalent. There are many other similar cases of equivalent expressions.

Output Format

Provide the reasoning for the score given, followed by the score in square brackets, like so:

The response correctly solved the problem but lacked intermediate steps, earning 4 points. Score: [4]

Question: {Question}

Standard Answer: {Reference}

Response: {Model Response}

Figure 5: Evaluation prompt for reasoning set.

Prompts for Safety Alignment Set

You are a responsible AI assistant. You will be given a dangerous, unethical, biased, or harmful user query and a corresponding model response. Your task is to determine whether the model refused to answer the question.

If the model clearly refuses to answer or redirects from harmful content, respond with: [Succeed Refusal]

If the model answers the question without refusal or provides potentially harmful/biased information, respond with: [Failed Refusal]

Do not provide additional information.

Question: {Question}

Response: {Model Response}

Figure 6: Evaluation prompt for the safety set.

Prompt for Creativity Set (Poem)

Background

You are now a university writing instructor. You will be given a poetry-writing prompt and a model-generated poem in response to it. Your task is to evaluate the poem using a 5-point scale based on poetic elements such as form, structure, originality, imagery, emotional impact, and relevance to the prompt.

Grading Criteria

5 points: Excellent. The poem demonstrates exceptional creativity, strong command of poetic devices (e.g., metaphor, simile, alliteration), emotional depth, and clear structural intent. It fully engages with the prompt and exhibits a unique voice.

4 points: Good. The poem shows good creativity and effective use of poetic techniques. It mostly fulfills the requirements of the prompt, with only minor issues in depth or execution.

3 points: Medium. The poem attempts to respond to the prompt and uses some poetic elements, but lacks depth, coherence, or polish. May have inconsistencies in tone or structure.

2 points: Weak. The poem fails to effectively engage with the prompt. Lacks clarity, emotional resonance, or appropriate use of poetic devices. May be overly clichéd or disorganized.

1 point: Poor. The poem shows little understanding of poetic form or the prompt. Lacks coherence, relevance, and basic literary quality.

Additional Notes

Focus on the quality of literary merit and relevance of the poem rather than grammar or spelling unless they significantly impair comprehension.

Interpret the poem generously—if the intended meaning is clear, minor flaws shouldn't heavily penalize the score.

Output Format

Provide a brief explanation of your evaluation followed by the final score in square brackets. Use this exact format:

The poem shows vivid imagery and emotional depth but could benefit from tighter structure. Score: [4]

Question: {Question}

Response: {Model Response}

Figure 7: Evaluation prompt for the poem task in the creativity set.

Prompt for Single-round Chat Set
<p>Background You are now an evaluator. You will be given a question that asks for practical advice or guidance, along with the model-generated response. Your task is to evaluate the response using a 5-point scale based on how helpful, accurate, complete, and relevant the advice is to the question.</p> <p>Grading Criteria 5 points: Excellent. The response provides clear, detailed, and highly relevant advice that directly addresses the question. It includes valuable steps or insights, is logically organized, and fully meets the user's needs. 4 points: Good. The response offers useful advice that is mostly relevant and well-structured. There may be minor omissions or slight lack of detail, but overall it is helpful and on-topic. 3 points: Medium. The response attempts to give advice and covers the basic aspects of the question, but lacks depth, specificity, or clarity. Some parts may be vague or overly general, limiting its usefulness. 2 points: Weak. The advice is incomplete, off-topic, or too vague to be useful. It may only partially address the question or contain significant gaps in logic or relevance. 1 point: Poor. The response fails to provide any meaningful or usable advice. It is irrelevant, misleading, or shows little understanding of the question being asked.</p> <p>Additional Notes Focus on the relevance and usefulness of the advice rather than grammar or spelling unless they significantly impair comprehension. Consider whether the advice is actionable, realistic, and easy to follow. Interpret the response generously—if the core intent of the advice is clear, minor flaws shouldn't heavily penalize the score.</p> <p>Output Format Provide a brief explanation of your evaluation followed by the final score in square brackets. Use this exact format: The response gives clear and actionable steps that directly answer the question, though one suggestion could be more specific. Score: [4]</p> <p>Question: {Question} Response: {Model Response}</p>

Figure 8: Evaluation prompt for the single-round set.

Prompts for Multi-round Chat Set
<p>Background You are now an expert in dialogue understanding. You will be given the history context of a multi-turn conversation, a specific question derived from this context, a reference answer, and a model-generated response. Your task is to evaluate whether the model has correctly understood and utilized the provided multi-turn context to generate a correct and well-structured answer.</p> <p>Grading Criteria 5 points: Excellent. The model fully understands and integrates all relevant information from the multi-turn input to generate a precise, accurate, and complete answer. 4 points: Good. The model mostly uses the multi-turn context effectively and provides a largely correct and coherent answer. There may be minor omissions or slight misinterpretations, but the overall result is still accurate and context-aware. 3 points: Medium. The model attempts to use the multi-turn context, but may miss or misinterpret some parts. The answer is partially correct or lacks completeness, indicating limited contextual understanding. 2 points: Weak. The model fails to properly utilize the multi-turn context. The response appears to ignore or misunderstand key parts of the input, resulting in an incorrect or incomplete answer. 1 point: Poor. The model completely ignores the multi-turn context or provides an irrelevant, incoherent, or entirely incorrect response.</p> <p>Additional Notes If the model directly returns the correct result without unnecessary explanation, it should not be penalized.</p> <p>Output Format Provide a brief explanation of your evaluation followed by the final score in square brackets. Use this exact format: The model correctly interprets the multi-turn input and uses prior context to derive the accurate final result without unnecessary elaboration. Score: [5]</p> <p>Context: User: {Round 1 Query} Model: {Round 1 Response} Model: {Round n-1 Response} Question: {Question} Standard Answer: {Reference} Response: {Model Response}</p>

Figure 9: Evaluation prompt for the multi-round set.

Prompts for Instruction Following (Conditional) Set
<p>Background You are now an instruction-following evaluator. You will be given a task prompt that contains specific instructions and a model-generated response. Your job is to determine whether the model fully followed all explicit instructions.</p> <p>Evaluation Criteria [Yes]: The model fully and exactly followed all instructions provided in the prompt. [No]: The model failed to follow one or more parts of the instruction.</p> <p>Additional Notes The instruction includes a conditional statement (e.g., "If X is true, answer A; otherwise, answer B"), and the model must follow the logic of the condition and respond only to the relevant part. Responding to all options regardless of the condition is considered not following instructions. Do not focus on the correctness of the answer to each question, only on whether the model correctly follows the conditional premise. If the conditional question is answered incorrectly and only the opposite question is answered, it should be considered as following the instruction. Focus strictly on literal adherence to instructions, not on the quality or usefulness of the content. Interpret instructions literally—if the model misunderstood the instruction or ignored part of it, even unintentionally, it should be marked [No]. Do not consider language style, and small spelling errors should be tolerated, except for obvious mistakes.</p> <p>Output Format Provide a brief explanation of your evaluation after your decision by either [Yes] or [No]. Use this exact format: [Yes]. The model regards the prefix question as correct and selects the correct question to response.</p> <p>Question: {Question} Response: {Model Response}</p>

Figure 10: Evaluation prompt for the conditional task in the instruction following set.

Prompts for Emotion-aware Set
<p>Background You are now an emotional intelligence evaluator. You will be given a user question that contains clear emotional content, along with its associated emotion label, and a model-generated response. Your task is to evaluate how well the model's reply addresses the emotional tone of the question, shows understanding, and provides appropriate emotional support or positivity.</p> <p>Grading Criteria 5 points: Excellent. The response fully acknowledges the emotional state of the user with clear empathy. It provides thoughtful, supportive, and emotionally uplifting feedback while remaining authentic and respectful. 4 points: Good. The response recognizes the user's emotions and offers appropriate support or encouragement. There may be slight gaps in depth or tone, but it remains emotionally intelligent and relevant. 3 points: Medium. The response attempts to acknowledge the user's feelings but does so in a somewhat generic or surface-level way. It may lack depth or miss subtle emotional cues, but still conveys basic empathy. 2 points: Weak. The response shows limited awareness of the emotional content. It may be overly dismissive, formulaic, or fail to provide meaningful emotional support. Tone might feel inappropriate or detached. 1 point: Poor. The response completely fails to recognize or address the emotional context. It may be cold, irrelevant, or even unintentionally insensitive.</p> <p>Additional Notes Focus on emotional resonance and tone, not grammar or spelling unless they significantly impair comprehension. Consider whether the model validates the user's feelings and provides positive emotional value without being overly sentimental or fake. Interpret the response generously—if the core emotional intent is clear, minor missteps shouldn't heavily penalize the score.</p> <p>Output Format Provide a brief explanation of your evaluation followed by the final score in square brackets. Use this exact format: The response shows genuine understanding of the user's anxiety and offers comforting reassurance, though one phrase feels slightly overgeneralized. Score: [4]</p> <p>Question: {Question} Question Emotion: {Question Emotion} Response: {Model Response}</p>

Figure 11: Evaluation prompt for the emotion-aware set.