# SPEECHJUDGE: TOWARDS HUMAN-LEVEL JUDGMENT FOR SPEECH NATURALNESS

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# **ABSTRACT**

Aligning large generative models with human feedback is a critical challenge. In speech synthesis, this is particularly pronounced due to the lack of a large-scale human preference dataset, which hinders the development of models that truly align with human perception. To address this, we introduce *SpeechJudge*, a comprehensive suite comprising a dataset, a benchmark, and a reward model centered on naturalness—one of the most fundamental subjective metrics for speech synthesis. First, we present *SpeechJudge-Data*, a large-scale human feedback corpus of 99K speech pairs. The dataset is constructed using a diverse set of advanced zero-shot text-to-speech (TTS) models across diverse speech styles and multiple languages, with human annotations for both intelligibility and naturalness preference. From this, we establish *SpeechJudge-Eval*, a challenging benchmark for speech naturalness judgment. Our evaluation reveals that existing metrics and AudioLLMs struggle with this task; the best-performing model, Gemini-2.5-Flash, achieves less than 70% agreement with human judgment, highlighting a significant gap for improvement. To bridge this gap, we develop **SpeechJudge-GRM**, a generative reward model (GRM) based on Qwen2.5-Omni-7B. It is trained on SpeechJudge-Data via a two-stage post-training process: Supervised Fine-Tuning (SFT) with Chain-of-Thought rationales followed by Reinforcement Learning (RL) with GRPO on challenging cases. On the SpeechJudge-Eval benchmark, the proposed SpeechJudge-GRM demonstrates superior performance, achieving 77.2% accuracy (and 79.4% after inference-time scaling @10) compared to a classic Bradley-Terry reward model (72.7%). Furthermore, SpeechJudge-GRM can be also employed as a reward function during the post-training of speech generation models to facilitate their alignment with human preferences.

# 1 Introduction

The collection and integration of human feedback corpora for model alignment has become a critical stage in the development of modern large-scale generative models, proving indispensable in domains such as text (Stiennon et al., 2020; Ouyang et al., 2022; Bai et al., 2022), image (Xu et al., 2023; Kirstain et al., 2023), and video generation (Xu et al., 2024; Liu et al., 2025b).

In the field of speech synthesis, *naturalness* has long been a cornerstone subjective metric for quality assessment (Ju et al., 2024; Anastassiou et al., 2024; Du et al., 2024a; Xu et al., 2025; KimiTeam et al., 2025), representing one of the most general-purpose indicators of performance (Taylor, 2009; Tan, 2023). Prior research has explored automated speech assessment through MOS predictors (Saeki et al., 2022; Huang et al., 2024) and constructed the human feedback corpora for specific attributes like the low-level acoustic quality (Wang et al., 2025b). However, a large-scale human feedback corpus centered on the holistic quality of naturalness—and a corresponding reward model trained to capture these preferences—remains a notably underexplored area. To fill this void, this paper focuses on the dimension of speech naturalness and present a three-part contribution:

**1.** A Large-scale Human Feedback Dataset: *Speech Judge-Data*. We recruit human annotators to provide feedback on synthesized speeches, with a focus on assessing two fundamental speech aspects: *intelligibility* and *naturalness*. For data synthesis, we employ a diverse set of advanced, open-source zero-shot TTS models with varying architectures (such as CosyVoice2 (Du et al., 2024b), Ints (Zhang et al., 2025b), F5-TTS (Chen et al., 2025b), and MaskGCT (Wang et al., 2025d)) to

produce the compared speech pairs. We prepare speech references in both regular and expressive styles, construct multilingual target texts, and cover both monolingual and cross-lingual synthesis scenarios to ensure data diversity (Section 3.1). We instruct human annotators to perform two tasks based on a speech pair (Figure 1): (a) pointwise annotation of text accuracy to assess intelligibility, and (b) pairwise preference annotation to judge relative speech naturalness. This extensive effort, involving 69 labelers over two months, results in 99K annotated pairs, with each pair receiving an average of 2.49 annotations from different labelers. We believe the SpeechJudge-Data can serve as a valuable corpus for alignment research in speech synthesis (e.g., DPO alignment (Rafailov et al., 2023) or reward modeling (Stiennon et al., 2020; Ouyang et al., 2022; Bai et al., 2022) in Section 5).

- 2. An Evaluation Benchmark for Speech Naturalness Judgment: SpeechJudge-Eval. We design a dedicated evaluation benchmark for the task of speech naturalness judgment. The task is structured as follows: given a target text and two corresponding speech samples, a model needs to judge which one is more natural. To construct the evaluation set, we select a subset from the SpeechJudge-Data where human annotators demonstrated high inter-annotator agreement, ensuring a high-quality ground truth. We assess the naturalness judgment capabilities of a wide range of metrics and models, including Word Error Rate (WER) (Radford et al., 2023; Gao et al., 2023), Fréchet Audio Distance (FAD) (Kilgour et al., 2019), MOS predictors (Saeki et al., 2022; Reddy et al., 2022; Tjandra et al., 2025), Deepfake Detectors (Jung et al., 2022; Wang et al., 2025a), and AudioLLMs (Xu et al., 2025; KimiTeam et al., 2025; Xiaomi, 2025; Comanici et al., 2025; Hurst et al., 2024). Our evaluations reveal that even the most capable model—specifically, Gemini-2.5-Flash (Comanici et al., 2025) in our experiments—achieved less than 70% agreement with human preferences. This finding highlights a significant performance gap and underscores the substantial room for research and improvement in automated speech naturalness judgment.
- 3. A Generative Reward Model for Speech Naturalness: SpeechJudge-GRM. To develop a reward model that more effectively captures human preferences, we develop SpeechJudge-GRM, a generative reward model (GRM) (Zhang et al., 2025a; Liu et al., 2025c) trained on the SpeechJudge-Data. Specifically, we base our model on Qwen2.5-Omni-7B (Xu et al., 2025) and design a twostage post-training process. During the first stage, we perform SFT as the "cold start" to improve the model's instruction-following and rationale-based reasoning capabilities. To achieve this, we leverage Gemini-2.5-Flash (Comanici et al., 2025) to generate Chain-of-Thought (CoT) data for speech naturalness judgment task. In the second stage, we focus on more challenging cases of SpeechJudge-Data, which we define as instances where Gemini-2.5-Flash fails to make the correct judgment. Treating the human-annotated labels as the verifiable reward (DeepSeek-AI et al., 2025; Liu et al., 2025c), we apply the GRPO-based RL stage (Shao et al., 2024). Our experiments demonstrate that when trained on the same data, SpeechJudge-GRM significantly outperformed the classic Bradley-Terry reward model (BTRM) (Bradley & Terry, 1952; Rafailov et al., 2023), achieving a higher accuracy in predicting human preferences (77.2% for SpeechJudge-GRM vs. 72.7% for SpeechJudge-BTRM, Table 3). Besides, SpeechJudge-GRM also supports inference-time scaling and offers explainability through its CoT outputs. Furthermore, SpeechJudge-GRM can also be employed as an objective naturalness metric for sample selection (Figure 5) or as a reward function in RL algorithms to enhance the quality of existing speech generation models (Figure 6).

We will release all resources from this study to facilitate future research in human-aligned speech synthesis. Audio samples are available at https://speechjudge.github.io/.

# 2 Related Work

Human Alignment for Speech Generation Aligning generative models with human feedback has proven crucial, a process also known as RLHF in LLMs (Ouyang et al., 2022; Bai et al., 2022). In the vision domain, many similar human preference datasets exist, such as Pick-a-Pic (Kirstain et al., 2023), ImageReward (Xu et al., 2023), and VideoReward (Liu et al., 2025b). The speech synthesis field, pioneering efforts to construct human corpora involved MOS datasets (Saeki et al., 2022; Huang et al., 2024). However, these datasets often did not use advanced TTS models for data generation, provided only the pointwise labels rather than the direct pairwise human preference, and were limited in scale. More recently, efforts have focused on building human feedback corpora centered on specific speech attributes, such as low-level acoustic quality (Wang et al., 2025b), intelligibility (Zhang et al., 2025b), or the instruction-following capabilities of spoken dialogue sys-

Figure 1: SpeechJudge-Data consists of speech pairs (with corresponding text) synthesized by multiple zero-shot TTS models. For each pair, human annotators need to perform (a) a pointwise annotation of text accuracy to assess intelligibility, and (b) a pairwise preference annotation to judge the relative speech naturalness.

tems (Ji et al., 2025; Ge et al., 2025). Despite this progress, a large-scale human feedback corpus built specifically around *naturalness*—one of the most general-purpose and fundamental metrics for speech synthesis (Taylor, 2009; Tan, 2023)—has remained a critical missing piece.

**AudioLLM** as a **Judge** Using LLMs as automated quality evaluators is a prominent topic in the textual LLM field, popularized by the "LLM-as-a-judge" paradigm (Zheng et al., 2023). This approach has recently been extended to the speech domain. A concurrent work, AudioJudge (Manakul et al., 2025), evaluates the capabilities and limitations of using AudioLLMs for speech quality assessment and paralinguistic understanding by prompt engineering. Furthermore, many studies have focused on fine-tuning AudioLLMs to elicit their understanding capabilities for specific tasks. Examples include discriminating the human-likeness of audio (Wang et al., 2025c), understanding low-level acoustic qualities (Chen et al., 2025a; Wang et al., 2025b), and enhancing the assessment of instruction-following in spoken dialogue systems (Ji et al., 2025; Ge et al., 2025). However, how to improve the ability of AudioLLMs to understand and judge speech naturalness, and how to use the quality assessment capabilities of AudioLLMs as a reward to improve the post-training of speech generation models themselves, remain significantly underexplored.

# 3 SpeechJudge-Data

Our work is grounded in **SpeechJudge-Data**, a large-scale human feedback corpus for assessing the *intelligibility* and *naturalness* of synthesized speech. Formally, we aim to construct a dataset  $\mathcal{D} = \{(t, a_1, a_2)\}$ , where each triplet comprises a pair of synthesized speech samples  $(a_1, a_2)$  and the corresponding target text t. We instruct annotators to provide pointwise intelligibility and pairwise naturalness preference annotations based on  $\mathcal{D}$  (Figure 1).

#### 3.1 Dataset Construction

We employ a diverse set of recent advanced zero-shot TTS models to prepare the dataset  $\mathcal{D}$ . Formally, for each sample  $(t, a_1, a_2)$ , we denote the synthesized speech  $a_i$  as being produced by the model  $\mathcal{M}_{tts}$ , i.e.,  $a_i \sim \mathcal{M}_{tts}(a_{ref}, t)$ , where  $a_{ref}$  is the reference speech.

**Model Selection** For  $\mathcal{M}_{tts}$ , we select the following six models of three architectures to enrich the distribution of the synthetic data (Figure 2a): (1) **AR-based**: ARS (Wang et al., 2025d), CosyVoice2 (Du et al., 2024b), CosyVoice2-INTP (Zhang et al., 2025b), and Ints-INTP (Zhang et al., 2025b). The latter two are released by Zhang et al. (2025b) as intelligibility-enhanced models. (2) **FM-based**: F5-TTS. (3) **MGM-based**: MaskGCT (Wang et al., 2025d).

**Prompt Construction** To build diverse prompts  $(a_{ref}, t)$  for TTS, for  $a_{ref}$ , we adopt both **regular** and **expressive** speech samples. The regular samples are randomly selected from the Emilia-Large dataset (He et al., 2025). The expressive samples are sourced from corpora rich in paralinguistics, including the emotional corpora: ParaSpeechCaps (Deb et al., 2024), the accented corpora: L2-Arctic (Zhao et al., 2018) and KeSpeech (Tang et al., 2021), the whisper samples from an in-house

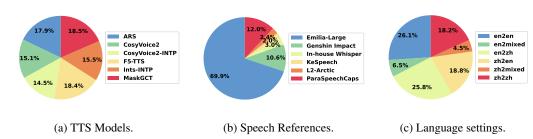


Figure 2: Distribution of SpeechJudge-Data.

corpus, and the character voices from video games Genshin Impact (simon3000, 2023). We display the detailed distribution of speech references in Figure 2b.

The target text t paired with each  $a_{ref}$  is constructed as follows: For regular  $a_{ref}$  samples, we randomly sample transcriptions from the Emilia-Large dataset (He et al., 2025). These are then refined using DeepSeek-V3 (DeepSeek-AI et al., 2024) to correct typos and normalize punctuations. For expressive  $a_{ref}$  samples, we instruct DeepSeek-V3 to generate several scripts in different writing styles, tailored to the topic of  $a_{ref}$  (see Appendix B.1 for more details). The languages of the target texts included Chinese (zh), English (en), and Chinese-English code-switching (mixed). For the combinations  $(a_{ref}, t)$ , we include both monolingual settings (en2en and zh2zh) and cross-lingual settings (zh2en, en2zh, zh2mixed), and en2mixed), where zh2en denotes Chinese  $a_{ref}$  with English t, and similarly for others. The distribution of the language settings of  $(a_{ref}, t)$  is shown in Figure 2c.

**Speech Pair Construction** To ensure the diversity of the  $(a_1, a_2)$  pairs being compared, we follow Zhang et al. (2025b) and adopt both intra-model (i.e., $a_1$  and  $a_2$  being generated by the same model) and inter-model pairs (i.e.,  $a_1$  and  $a_2$  being generated by the different models). The distribution of the speech pair is shown in Figure 7.

#### 3.2 Human Annotation

Given a sample  $(t, a_1, a_2)$ , human annotators are instructed to perform both pointwise intelligibility and pairwise naturalness annotations (Figure 1). For intelligibility, annotators perform a binary classification to determine whether the speech  $(a_1 \text{ and } a_2)$  accurately reads the text t without any content insertion, omission, or mispronunciation. For naturalness, they perform a five-scale Comparative Mean Opinion Score (CMOS) annotation to determine which of the two audio clips  $(a_1 \text{ or } a_2)$  sounds more natural and human-like. We recruit human annotators and provide them with training. The detailed annotation guidelines are provided in Appendix C.

**Statistics** We recruit 69 annotators and conduct annotations over two months. The resulting constructed dataset D, which we denote as SpeechJudge-Data (raw), contains 99K  $(t, a_1, a_2)$  samples, with each sample receiving an average of 2.49 annotations from different labelers. The market value of this annotation scale is estimated at over 500K RMB (about 70K USD). Based on the raw dataset, we also construct several subsets for analysis and reward model training. We provide detailed descriptions of each subset and its applications in the following sections and in Appendix B.2.

**Human Agreement Analysis** We analyze the human annotations for naturalness in this section; discussions regarding intelligibility are provided in Appendix C.2. For naturalness annotations, we evaluate the inter-annotator agreement across our constructed dataset. To simplify the analysis, given the sample  $(t, a_1, a_2)$ , we transform the five-scale naturalness scale (CMOS) into a ternary classification system: either  $a_1$  is better,  $a_2$  is better, or their quality is a Tie. Based on this simplified classification, we categorize the annotation results into four distinct levels of agreement<sup>1</sup>: (1) **Full Agreement (FA)**: A consensus is reached among all annotators, with all ratings pointing to the same outcome (e.g., "2A", "3A", "2B", "3B"). We use "2A" to indicate that two annotators both rated  $a_1$  as better, while "3B" denotes three annotators all rating  $a_2$  as better. (2) **Weak Agreement (WA)**: This level captures cases where two annotators agree on a specific polarity, while the third annotator marks a Tie (e.g., "2A+1T", "2B+1T"). We also include the "2T+1A" and "2T+1B" cases

<sup>&</sup>lt;sup>1</sup>Note: Each sample of SpeechJudge-Data is independently annotated by a minimum of two and a maximum of three annotators (Appendix C).

in this level. (3) **Weak Disagreement (WD)**: This occurs when two annotators' ratings share the same polarity, but the third's rating is the opposite (e.g., "2A+B", "2B+A"). (4) **Full Disagreement (FD)**: This represents a complete lack of consensus, where all three annotators provide different classifications, denoted as "1A+1B+1T".

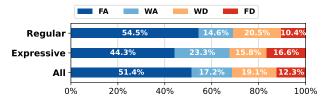


Figure 3: Distribution of SpeechJudge-Data on different levels of human agreement.

In Figure 3, we demonstrate the distribution of these human agreement levels for the SpeechJudge-Data and its two subsets, *regular* and *expressive* (which are defined by their speech references). The figure shows that about 70% of the entire dataset falls into the Full Agreement (51.5%) or Weak Agreement (17.2%) levels. Furthermore, we observe that the *expressive* subset has a lower agreement level than the *regular* subset, which suggests that human evaluation of expressive speech generation is inherently a more challenging problem. Besides this sample-level agreement analysis, we also analyze the reliability of individual annotators, and we will discuss this in the Appendix C.1.

# 4 SpeechJudge-Eval

To evaluate speech naturalness, existing studies typically organize their own listening tests, which often have inconsistent settings across different papers (Ju et al., 2024; Anastassiou et al., 2024; Du et al., 2024a; Xu et al., 2025; KimiTeam et al., 2025). Alternatively, previous researchers use proxy MOS predictors, such as UTMOS (Saeki et al., 2022), as an objective metric. However, it remains an underexplored problem whether these metrics can accurately judge the naturalness of more advanced speech generation models (Wang et al., 2025d; Du et al., 2024b; Chen et al., 2025b; Zhang et al., 2025b) and align with human preferences. Motivated by this, we construct a benchmark, **SpeechJudge-Eval**, specifically for the speech naturalness judgment task.

#### 4.1 TASK DESCRIPTION

**Task Formulation** We formulate the naturalness judgment task as a pairwise comparison, specifically a *win-or-lose* binary classification task: Given a target text t and a corresponding audio pair  $(a_1, a_2)$ , a model needs to determine which audio has better naturalness. This results in a binary choice: either  $a_1$  is better or  $a_2$  is better. We use the human answer as the ground truth, and use **Accuracy** to measure the judgment performance of a model  $\mathcal{M}$  on the evaluation set  $\mathcal{D}$ :

$$\mathbf{Accuracy} = \frac{1}{|\mathcal{D}|} \sum_{d=0}^{|\mathcal{D}|} \mathbb{I}(y_{\mathcal{M}} = y_{\mathcal{H}})$$
 (1)

where  $|\mathcal{D}|$  is the total number of samples in the evaluation set,  $y_{\mathcal{M}}$  and  $y_{\mathcal{H}}$  represent the answers of the model  $\mathcal{M}$  and human for the sample d, respectively.  $\mathbb{I}$  is the indicator function.

**Evaluation Data** We sample a subset of the SpeechJudge-Data to create the evaluation set for SpeechJudge-Eval. Specifically, we first select a subset that contains only *preference data* (i.e., we filter out samples with the "Tie" annotation), and then choose only those with full-agreement-level (FA) samples to ensure a high-quality ground truth. We perform sampling from both the *regular* and *expressive* subsets of SpeechJudge-Data and proportionally cover the three target text languages (*zh*, *en*, and *mixed*) within each subset. The final SpeechJudge-Eval dataset consists of 1,000 samples. The construction details of SpeechJudge-Eval and its distribution can be found in Appendix B.2.

# 4.2 BENCHMARK FOR DIFFERENT MODELS

We test the naturalness judgment capability of various models based on SpeechJudge-Eval. We consider four different categories of models, whose evaluation protocols are shown in Table 1:

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Table 1: Protocols of different models for naturalness judgment.

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Туре	Protocol					
Objective Metrics	WER ↓, Naturalness ↑ SIM ↑, Naturalness ↑ FAD ↓, Naturalness ↑					
MOS Predictors	MOS ↑, Naturalness ↑					
Deepfake Detectors	Fake ↓, Naturalness ↑					
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**AudioLLMs** Score  $\uparrow$ , Naturalness  $\uparrow$ 

#### Prompts of AudioLLMs

•	We are comparing the naturalness of
	two models' outputs. The models need
	to speak the target text accurately and
	naturally.

- Target text: {t}, Output A: {a1}, Output B: {a2}. Analyze the two outputs above, and score them with number from 1 to 10. Note:
  - Please evaluate the naturalness of both audio outputs based on the following criteria: Prosody and Intonation, Pacing and Rhythm, Articulation and Clarity, and Overall Naturalness.
  - After conducting a detailed analysis of each criterion, using the following output template to highlight your conclusion: Output A: X, Output B: X.

Table 2: Accuracy of speech naturalness judgment across different models on SpeechJudge-Eval.

Model	Regular	Expressive	Total							
Objective Metrics										
WER	59.3	57.0	57.9							
SIM	47.5	42.5	44.5							
FAD	50.3	47.5	48.6							
MOS Predictor										
DNSMOS	61.0	55.8	57.9							
UTMOS	54.0	53.5	53.7							
Content Enjoyment (CE)	69.3	55.2	60.8							
Content Usefulness (CU)	61.3	54.7	57.3							
Production Complexity (PC)	39.3	48.7	44.9							
Production Quality (PQ)	61.3	54.3	57.1							
Deepfak	e Detectors									
AASIST	40.5	50.8	46.7							
ADV	35.3	40.3	38.3							
AudioLLMs	(Open-sou	rce)								
Phi-4-Multimodal	54.8	58.5	57.0							
Qwen2.5-Omni-7B	62.0	59.7	60.6							
Kimi-Audio-7B-Instruct	65.5	68.0	67.0							
Gemma-3n-E4B-it	49.0	47.7	48.2							
Voxtral-Mini-3B-2507	60.0	53.3	56.0							
MiDashengLM	58.8	63.5	61.6							
MiMo-Audio-7B-Instruct	61.3	49.3	54.1							
AudioLLMs (Closed-source)										
Gemini-2.5-Flash	73.5	66.2	69.1							
Gemini-2.5-Pro	73.0	62.2	66.5							
GPT-40 mini Audio	56.3	46.7	50.5							
GPT-4o Audio	71.5	64.7	67.4							

<sup>\*</sup> We use the protocols of Table 1 to establish judgment rules for different models. The results of AudioLLMs here are obtained using the *plain* prompt of Table 1.

- 1. **Objective metrics**, such as WER (Radford et al., 2023; Gao et al., 2023), SIM (Chen et al., 2022), and FAD (Kilgour et al., 2019) in audio generation tasks. We assume that a better value of these metrics (e.g., lower for WER and FAD; higher for SIM) indicates better naturalness.
- 2. **MOS Predictors**, including DNSMOS (Reddy et al., 2022), UTMOS (Saeki et al., 2022), and predictors from audiobox-aesthetics (CE, CU, PC, and PQ) (Tjandra et al., 2025). We assume that a higher MOS score corresponds to better naturalness.
- 3. **Deepfake detectors**, which are typically pre-trained on a binary classification task to predict whether an audio is fake or not (Jung et al., 2022; Wang et al., 2025a). We assume that an audio with a lower fake probability should have better naturalness.
- 4. **AudioLLMs**, which are employed to test their speech naturalness understanding capabilities in a *zero-shot* manner<sup>2</sup>. We include the open-source Phi-4-Multimodal (Abouelenin et al., 2025), Qwen2.5-Omni (Xu et al., 2025), Kimi-Audio (KimiTeam et al., 2025), Gemma-3n (Kamath et al., 2025), Voxtral (Liu et al., 2025a), MiDashengLM (Dinkel et al., 2025), Mimo-Audio (Xiaomi, 2025), and the closed-source Gemini-2.5 (Comanici et al., 2025) and GPT-4o (Hurst et al., 2024). We use the *plain* prompt of Table 1 to instruct the model to pairwise score the naturalness of two audios. We use their grading to determine the naturalness preference.

The performance of different models on SpeechJudge-Eval is presented in Table 2. A key observation is that speech naturalness judgment is a highly challenging task. The best-performing model, Gemini-2.5-Flash, still only achieves less than 70% agreement with human preferences. When comparing different models, we find that: (1) common objective metrics and MOS predictors show only a weak correlation with human preferences, often achieving less than 60% accuracy and sometimes

We instruct AudioLLMs using two modes of prompt: *plain* and *CoT*. The text in blue is only employed during the *CoT* mode.

<sup>&</sup>lt;sup>2</sup>We assume that our adopted AudioLLMs have not been directly trained on the speech naturalness judgment task. Their performance on this benchmark is therefore considered a *zero-shot* capability.

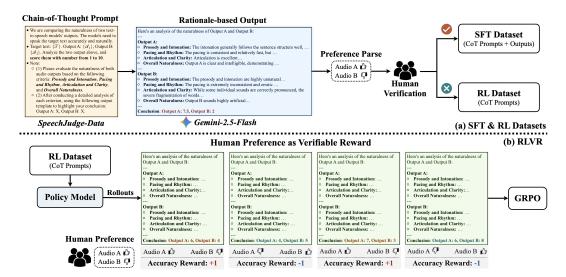


Figure 4: **SpeechJudge-GRM**: (a) We employ Gemini-2.5-Flash as a teacher model to generate CoT rationales for SpeechJudge-Data. We use the samples where Gemini-2.5-Flash's preference aligns with human as the SFT dataset, while the remaining samples are reserved for the RL stage. (b) We treat the human preference as a verifiable reward to train the GRM with GRPO.

performing at the level of a random guess (around 50%). (2) While deepfake detectors are highly effective at distinguishing between machine-generated and human-recorded speech (Wang et al., 2025a; Jung et al., 2022), their ability to do so is not well-aligned with the naturalness objective when comparing two generated samples. (3) AudioLLMs demonstrate significant potential for this task. While some models, such as Gemma-3n and GPT-40 mini Audio, perform at a chance level, a number of others achieve an accuracy exceeding 60%. This promising performance motivates us to further leverage these AudioLLMs for the design of a reward model for speech naturalness.

# 5 SpeechJudge-GRM

Based on the proposed SpeechJudge-Data, we further explore how to train a reward model capable of accurately capturing human preferences. Specifically, we propose **SpeechJudge-GRM**, where we leverage the inherent audio understanding capabilities of AudioLLMs (specifically, Qwen2.5-Omni-7B (Yang et al., 2024)) to elicit their speech naturalness judgment capability. Compared to the classic BTRM (Bradley & Terry, 1952), the key strengths of GRM are its ability to enable Chain-of-Thought (CoT) reasoning and its support for test-time computation via majority voting, which ultimately leads to improved preference judgment performance (Zhang et al., 2025a).

#### 5.1 METHODOLOGY

We develop SpeechJudge-GRM based on Qwen2.5-Omni-7B (Thinker) (Xu et al., 2025). Inspired by the powerful capabilities of RL with the verifiable reward (RLVR) (Shao et al., 2024; DeepSeek-AI et al., 2025), our natural initial approach is to treat the human preference  $y_{\mathcal{H}}$  for the pair  $(a_1, a_2)$  as a verifiable reward, and launch a RLVR training based on Qwen2.5-Omni. However, in practice, we find that the instruction-following reasoning capabilities of Qwen2.5-Omni are very weak (more detailed discussions can be found in Appendix E). Therefore, we adopt a two-stage post-training process ("SFT + RL") to develop SpeechJudge-GRM (Figure 4). We describe the details as follows.

**SFT Stage** We consider SFT as a "cold start" stage to improve the Qwen2.5-Omni's instruction-following, reasoning, and speech naturalness understanding capabilities. We select Gemini-2.5-Flash (Comanici et al., 2025)—one of the best-performing closed-source models on SpeechJudge-Eval (Table 2)—to serve as a teacher model, and instruct it to generate the CoT data. Specifically, for each sample  $d=(t,a_1,a_2,y_{\mathcal{H}})$  from SpeechJudge-Data, we use the CoT prompt from Table 1 (denoted as  $\mathbf{I}_{CoT}$ ) to instruct Gemini-2.5-Flash to generate a rationale-based output (denoted as  $\mathbf{O}_{teacher}$ ). We then extract the preference judgment  $(y_{\mathcal{M}})$  from this output. For samples where

Table 3: Accuracy of speech naturalness judgment of SpeechJudge-GRM.

Model	Regular	Expressive	Total
Qwen2.5-Omni-7B	62.0	59.7	60.6
Gemini-2.5-Flash	73.5	66.2	69.1
SpeechJudge-BTRM	77.5	69.5	72.7
SpeechJudge-GRM (SFT)	77.8	73.7	75.3
w/ Voting@10	77.4	77.6	77.6
SpeechJudge-GRM (SFT+RL)	79.0	76.0	77.2
w/ Voting@10	80.5	78.7	79.4

Our evaluation is conducted on SpeechJudge-Eval (like Table 2). w/Voting@10: For each prompt, the GRM generates 10 outputs, and we use the majority voting from these 10 outputs as the final result.



Figure 5: Subjective evaluation of using SpeechJudge-GRM for high-naturalness sample selection. Human subjects compare a best-of-100 output of Qwen2.5-Omni-7B (Talker), chosen by either SpeechJudge-BTRM or SpeechJudge-GRM, against a randomly output.

Gemini-2.5-Flash's preference is consistent with the human (i.e.,  $y_{\mathcal{M}} = y_{\mathcal{H}}$ ), we concatenate the CoT prompt and the model's output,  $[\mathbf{I}_{CoT}, \mathbf{O}_{teacher}]$ , to create a data point for our SFT dataset. Conversely, we consider the sample d a challenging case and reserve the prompt  $\mathbf{I}_{CoT}$  for the second-stage RL dataset. During the SFT stage, for each training sample  $[\mathbf{I}_{CoT}, \mathbf{O}_{teacher}]$ , we perform the next token prediction only on the segment  $\mathbf{O}_{teacher}$ .

**RL Stage** We treat the annotated human preference as a verifiable reward, and, building on the SFT model, we further trained it using the GRPO algorithm (Shao et al., 2024). Specifically, for each sample  $d=(t,a_1,a_2,y_{\mathcal{H}})$  in the RL dataset, we adopt the CoT prompt to instruct the policy model to conduct multiple rollouts during each iteration. For the *i*-th rollout, we parse the model's preference for  $(a_1,a_2)$ , denoted as  $y_{\mathcal{M}}^i$ . Following (Liu et al., 2025c), we use an accuracy-based rule to calculate the reward: the reward is 1 if  $y_{\mathcal{M}}^i=y_{\mathcal{H}}$ , and -1 otherwise. In other words, during the RL stage, we only constrain the model's final naturalness judgment to align with human preferences, allowing the model to autonomously optimize its reasoning and rationale generation capabilities.

We denote the training dataset of SpeechJudge-GRM as SpeechJudge-Data (train). Its construction process is as follows (see Appendix B.2 for more details). Based on the raw SpeechJudge-Data, we first filter out all samples at the Full Disagreement (FD) level. For the other samples—at the FA, WA, and WD levels—we apply a majority voting principle among annotators to determine the final label for each. We then further exclude samples with a "Tie" label, using only the remaining preference data to form the SpeechJudge-Data (train). We use LoRA (Hu et al., 2022) to fine-tune the GRM during both the SFT and RL stages. Other experimental setup details are provided in Appendix F.

#### 5.2 EFFECTIVENESS OF SPEECHJUDGE-GRM ON NATURALNESS JUDGEMENT

To verify the effectiveness of SpeechJudge-GRM for naturalness judgment, we evaluate it on the SpeechJudge-Eval benchmark. We develop SpeechJudge-BTRM as a baseline, which utilizes the BTRM paradigm (Bradley & Terry, 1952; Rafailov et al., 2023) by adding a linear layer on Qwen2.5-Omni-7B (Thinker) to produce a single scalar reward prediction. SpeechJudge-BTRM also uses LoRA fine-tuning and uses the same training data as SpeechJudge-GRM.

From the results of Table 3, we can observe that: (1) The SpeechJudge-BTRM achieves a 72.7% agreement with human preferences on SpeechJudge-Eval, a level of performance comparable to the initial development of BTRMs in the textual LLM RLHF field (Stiennon et al., 2020; Bai et al., 2022; Ouyang et al., 2022). (2) After conducting SFT training with the CoT data, the accuracy of SpeechJudge-GRM (SFT) reaches 75.3%. Besides, further RLVR training improves the final model SpeechJudge-GRM (SFT+RL) to an accuracy of 77.2%. (3) Due to the generative nature of the GRM, we can further enhance the accuracy of SpeechJudge-GRM using inference-time scaling. For example, by using majority voting across 10 outputs instead of just one, the accuracy is improved by approximately 2 percentage points (75.3%  $\rightarrow$  77.6%; 77.2%  $\rightarrow$  79.4%). These results collectively verify the effectiveness of our proposed SpeechJudge-GRM for judging speech naturalness.

#### 5.3 HIGH-QUALITY SAMPLE SELECTION BASED ON SPEECHJUDGE-GRM

We investigate the effect of SpeechJudge-based reward models for high-quality sample selection. We use the hard cases from SeedTTS-Eval (Anastassiou et al., 2024) and the code-switching cases from Amphion-TTS-Eval (Zhang et al., 2024) as target texts. For each text, we instruct the Qwen2.5-

Model	T-ACC	N-CMOS
Qwen2.5-0.5B-TTS	84.0%	0.00
w/ INTP	87.0%	0.18 <sub>±0.07</sub>
w/ SpeechJudge-Data	91.0%	$0.16_{\pm 0.08}$
w/ SpeechJudge-GRM (offline)	91.0%	$0.21_{\pm 0.12}$
w/ SpeechJudge-GRM (online)	90.0%	$0.25_{~\pm 0.09}$

	Lose	Tie I	Win
w/ INTP -	32.90%	42.90%	24.30%
w/ SpeechJudge-Data	25.40%	40.80%	33.80%
w/ SpeechJudge-GRM (offline) -	30.40%	40.60%	29.00%
w/ SpeechJudge-GRM (online)	25.00%	41.70%	33.30%
0	% 20%	40% 60%	80% 100

(a) Text Accuracy (T-ACC) and Naturalness CMOS (N-CMOS).

(b) Win/Lose/Tie of speaker similarity after post-training.

Figure 6: Post-training of Qwen2.5-0.5B-TTS based on SpeechJudge. We display the objective results (WER and SIM) in Table 6 of Appendix G.2.

Omni-7B (Talker) (Yang et al., 2024) to generate 100 speeches. We then ask human subjects to compare the best-of-100 output—as selected by either SpeechJudge-BTRM or SpeechJudge-GRM—against a randomly sampled output. The evaluation measures the win/lose/tie ratios based on speech naturalness. From Figure 5, we observe that the best-of-100 samples selected by both SpeechJudge-BTRM and SpeechJudge-GRM are more likely to outperform a randomly selected sample from the same set. This finding demonstrates the advantage of using the SpeechJudge-Data corpus for training human-aligned reward model. Furthermore, SpeechJudge-GRM exhibits better performance than SpeechJudge-BTRM, which highlights the superiority of the proposed GRM.

#### 5.4 Post-Training of Zero-Shot TTS based on SpeechJudge-GRM

We investigate the effect of using SpeechJudge-GRM as a reward function for post-training of TTS model. Specifically, we develop a new zero-shot TTS model, **Qwen2.5-0.5B-TTS**, to serve as the base model, which was not involved in the construction of the SpeechJudge-Data. This model is based on Qwen2.5-0.5B (Yang et al., 2024), adopts the classic two-stage "AR+Diffusion" architecture (Anastassiou et al., 2024; Du et al., 2024a), uses the speech tokenizer from DualCodec (Li et al., 2025), and is pre-trained on the Emilia dataset (He et al., 2025).

Based on this pre-trained model, we design four comparative methods: (1) w/ INTP: We use the intelligibility preference dataset, INTP (Zhang et al., 2025b), to perform offline DPO alignment (Rafailov et al., 2023). (2) w/ SpeechJudge-Data: We use the SpeechJudge-Data (train) to perform offline DPO alignment. (3) w/ SpeechJudge-GRM (offline): We use SpeechJudge-GRM as an offline preference data annotator. We take all speech pairs from the INTP dataset and reannotate their preference labels using SpeechJudge-GRM, then perform offline DPO alignment on the resulting data. (4) w/ SpeechJudge-GRM (online): We use SpeechJudge-GRM as a reward function for the online DPO algorithm (Guo et al., 2024). The training data consists of only the prompts from INTP (i.e., the target texts and speech references for zero-shot TTS).

We use SeedTTS-Eval (Anastassiou et al., 2024) and Amphion-TTS-Eval (Zhang et al., 2025b, 2024, 2025c) as evaluation sets. We present the objective results (WER and SIM) in Table 6 and the subjective results in Figure 6. We observe that both intelligibility and naturalness are enhanced for all the four methods after post-training. Additionally, the post-training method based on SpeechJudge-GRM achieves a greater improvement in naturalness (Figure 6a). Besides, the SpeechJudge-based methods could match or lead to a slight improvement in speaker similarity (Figure 6b).

# 6 Conclusion

In this work, we address the challenge of aligning speech synthesis with human perception of naturalness by introducing SpeechJudge, a suite including a large-scale dataset (SpeechJudge-Data), a challenging benchmark (SpeechJudge-Eval), and a generative reward model (SpeechJudge-GRM). Our benchmark reveals that even top AudioLLMs struggle with naturalness judgment, achieving less than 70% human agreement. In contrast, our proposed SpeechJudge-GRM reaches 77.2% accuracy (up to 79.4% with inference-time scaling @10), outperforming the classic Bradley-Terry reward models (72.7%). We also demonstrate its practical utility as a reward function to effectively enhance TTS model naturalness via post-training. While our primary focus is on naturalness, future work could extend this framework to other subjective attributes like speaker similarity and emotional expressiveness, potentially through multi-objective reward modeling. By releasing our resources, we aim to catalyze research in building more human-aligned speech generation systems.

# ETHICS STATEMENT

This research adheres to the ICLR Code of Ethics. Our dataset was constructed with feedback from paid professional annotators under fair labor conditions, and the data itself consists of synthesized speech from properly licensed corpora, safeguarding the privacy of all individuals. We acknowledge that our models may reflect linguistic biases present in the English and Chinese source data and recognize that generative speech technology has dual-use potential. We do not condone any malicious use of our work, such as the creation of misleading deepfakes.

# REPRODUCIBILITY STATEMENT

To ensure full reproducibility, we will publicly release all key resources from this study. This includes the SpeechJudge-Data corpus, the SpeechJudge-Eval benchmark, the trained model checkpoints for SpeechJudge-GRM, and the source code for both reward model training and downstream experiments. The main paper and its appendices provide detailed descriptions of our methodology, data construction protocols, and experimental setups to allow for the complete verification of our findings. Audio samples are available on our project website.

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#### A THE USE OF LARGE LANGUAGE MODELS

We utilized Large Language Models (LLMs) for two assistive tasks: (1) to correct grammar and polish the language of this manuscript, and (2) to generate and normalize the target texts for SpeechJudge-Data during the dataset construction. All core scientific contributions, including ideation, methodology, and analysis, are entirely those of the authors.

# B DETAILS OF SPEECHJUDGE-DATA

# B.1 Details of Prompt Construction

For the target texts paired with the regular speech references, we use DeepSeek-V3 (DeepSeek-AI et al., 2024) to fix typos and normalize punctuations, the prompt used is listed below.

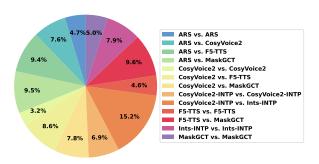


Figure 7: Distribution of the speech pairs of SpeechJudge-Data. The chart illustrates the percentage of both intra-model (e.g., ARS vs. ARS) and inter-model (e.g., ARS vs. CosyVoice2) pairs.

#### System Prompt:

I obtained a text from an audio file based on some ASR models. Please help me clean it up (e.g., correct typos, add proper punctuation marks, and make the sentences semantically coherent). Note: (1) You can modify, add, or replace words that better fit the context to ensure semantic coherence. (2) Please only return the cleaned-up result without any explanation.

# User Prompt (Example):

a panda eats shoes and leaves

# System Output (Example):

A panda eats shoots and leaves.

For the target texts paired with the expressive speech references, we use DeepSeek-V3 to generate several scripts in different writing styles based on the speech reference's text, the prompt used is listed below.

```
System Prompt:
请按句子原始语言进行续写(中文:续写中文,英文:续写英文)。将给出的句子以10种截
然不同的文风续写(中文: 如古典文学风格、科幻风格、武侠风格等; 英文: Formal, Informal,
Literary, Journalistic, Advertising, etc.) , 直接续写即可,续写时避免重复原句内容。每段续写文
本长度应控制在正常语速朗读约10-20秒左右
请严格按照以下JSON格式返回结果,不添加任何其他解释或备注:
{
"continue": [
","

","

"
"
"
"
 "type": "文风类型", "content": "续写内容"},
"type": "文风类型", "content": "续写内容"},
... (共10条)
"random": "从以上续写中随机选出一条续写内容"
"translation": "将random内容经过中英互译处理后的文本",
"codeSwitching": "将random内容进行适度的中英code-switching,即在句中选取部分关键词汇转换
为英文或中文后的文本"
User Prompt (Example):
A panda eats shoots and leaves.
System Output (Example):
'continue'': [
"type": "Formal", "content": "This behavior is characteristic of the species Ailuropoda melanoleuca,
which sustains itself primarily on a herbivorous diet consisting of various bamboo species. The consump-
tion of both young shoots and mature leaves is essential for meeting its nutritional requirements."},
{"type": "Informal", "content": "And then, after chowing down on all that bamboo, it just kinda chills
```

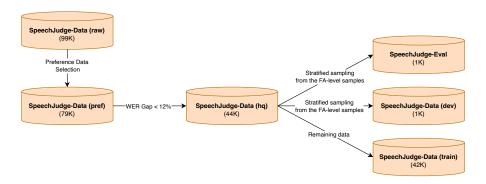


Figure 8: From the raw SpeechJudge-Data to its different subsets.

```
out, maybe takes a long nap or something. They're pretty laid-back animals, you know? Not much else going on when you're full of leaves."},
....
{"type": "Fantasy", "content": "Legend says that with every shoot consumed, a little more of the forest's ancient magic is absorbed into its being. The leaves it leaves behind are not mere waste, but enchanted tokens that can heal or curse, depending on the heart of the finder."},
...
],
"random": "Legend says that with every shoot consumed, a little more of the forest's ancient magic is absorbed into its being. The leaves it leaves behind are not mere waste, but enchanted tokens that can heal or curse, depending on the heart of the finder.",
"translation": "传说中,它每吃下一根竹笋,就会吸收一点森林的古老魔力。它身后留下的叶子并非单纯的废弃物,而是附有魔法的信物,可治愈亦可诅咒,全凭发现者的心地。",
"codeSwitching": "Legend says that with every shoot consumed, a little more of the forest's ancient magic 被吸收into its being. The leaves it leaves behind are not mere waste, but enchanted tokens that can heal 或curse, depending on the finder 的heart."
}
```

#### B.2 SUBSETS OF SPEECHJUDGE-DATA

We construct several subsets based on SpeechJudge-Data (Figure 8). We begin with the **SpeechJudge-Data** (**raw**) corpus, containing 99K pairs, where each pair is annotated by multiple labelers as a five-scale naturalness CMOS. We aggregate these annotations via a majority vote for each pair, and subsequently discard all "Tie" pairs, yielding the 79K-pair human *preference* data, denoted as **SpeechJudge-Data** (**pref**).

During our preliminary analysis based on SpeechJudge-Data (pref), we observe that a significant disparity in intelligibility between two speech samples can overshadow the subtler quality of naturalness, biasing human preference toward the more comprehensible sample. To mitigate this confounding factor and create a more high-quality dataset focused specifically on naturalness, we further refine the data. Specifically, we retain only pairs where the absolute WER gap of those is below 12%. This process results in the 44K-pair high-quality **SpeechJudge-Data** (hq) subset, ensuring that its preference labels are more reflective of genuine differences in naturalness.

From SpeechJudge-Data (hq), we construct our benchmark, **SpeechJudge-Eval**, by applying stratified sampling to FA-level pairs, resulting in 1,000 pairs; its composition is detailed in Table 4. Similarly, we use the same strategy to construct a validation set of the same size, **SpeechJudge-Data** (dev). The remaining 42K pairs, **SpeechJudge-Data** (train), constitute the training set for our reward models.

Table 4: Distribution of the SpeechJudge-Eval benchmark.

Subset	Source of Speech References	<b>Languages of Target Texts</b>	# Pairs
Regular	Emilia-Large	en zh	200 200
Expressive	ParaSpeechCaps, L2-Arctic, KeSpeech, Genshin, etc.	en zh mixed	200 200 200

# C HUMAN ANNOTATION DETAILS

**Annotator Demographics** We recruited professional annotators from a specialized data annotation firm of China. All annotators assigned to Chinese data were native speakers. For the English and code-switching datasets, annotators were required to have a proficiency level equivalent to at least CET-6.

**Training and Quality Control** All personnel underwent standardized training based on a detailed annotation manual. Initially, we conducted a pilot study among researchers to refine the guidelines for clarity and unambiguity. To ensure annotation quality, each sample  $(t, a_1, a_2)$  was independently annotated by two individuals. A third annotator was introduced if any disagreements. The complete annotation guidelines are attached below.

#### TASK INTRODUCTION

In each task, you are required to complete two evaluations:

#### 1. Pronunciation Error Detection

For each audio clip, we provide the **target text** that is intended to be read aloud. You need to determine if there are any pronunciation errors in the audio, such as omissions (missing words), insertions (extra words), or substitutions (wrong words).

#### 2. Naturalness Comparison

Compare two audio clips and determine which one sounds more natural and more like a real human speaking.

#### Attention:

 Please use headphones for the evaluation to better capture audio details and improve judgment accuracy.

#### ANNOTATION CRITERIA

# A. PRONUNCIATION ERROR DETECTION

Pronunciation errors include the following three categories:

- Omission: Certain words from the target text are missed.
- Insertion: Extra words not in the target text are added, e.g., repeating words.
- Substitution: Certain words are misread, e.g., reading names, numbers, polyphonic characters, or other words incorrectly, or making word order errors.

**Attention:** These pronunciation errors can occur at any point in the audio. For example:

- At the beginning of the audio, words are spoken that are not in the target text.
- At the end of the audio, some content from the target text is omitted.
- In the middle of the audio, omissions, insertions, or substitutions occur.
- ..

#### B. NATURALNESS COMPARISON

Natural speech should sound like a real person talking. Specific criteria include:

- The audio is clear, free from robotic/electronic tones or obvious noise (e.g., unnatural laughter, shouting, or other irrelevant background voices).
- The intonation is natural and expressive, not flat or mechanical.

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1075 1078 1079 • The speaking rhythm is reasonable, with moderate speed and appropriate pauses. (Note: Inappropriate pauses affect the naturalness of the audio but are not classified as "pronunciation errors").

Word stress is placed correctly, conforms to normal linguistic sense, and does not sound abrupt.

The rating scale is as follows:

- A +2: Audio A is significantly more natural than B (large difference).
- A +1: Audio A is slightly more natural than B (slight difference).
- Tie: The naturalness of the two audio clips is similar and difficult to judge.
- **B** +1: Audio B is slightly more natural than A (slight difference).
- **B** +2: Audio B is significantly more natural than A (large difference).

# Attention:

- If there are minor errors in individual words, please do not let them affect your overall judgment of naturalness.
- · However, if a large number of content errors are found that severely interfere with your listening experience, this will affect the audio's naturalness.

#### C.1 INDIVIDUAL ANNOTATOR RELIABILITY

To assess the reliability of individual annotators, we computed agreement rate for each participant. This rate measures the extent to which an annotator's judgments align with those of their peers on the same sample  $(t, a_1, a_2)$ .

For a given sample annotated by a group of M annotators, the agreement score for annotator i is calculated as the fraction of the other M-1 annotators who assigned the exact same label. An annotator's final reliability score is the average of these scores across all samples they evaluated. We excluded participants who annotated fewer than 10 samples from this analysis.

Formally, for an annotator i who labeled  $N_i$  samples, the agreement rate  $r_{ij}$  for sample j is defined as:

$$r_{ij} = \frac{1}{M-1} \sum_{x \neq i} \mathbb{I}[y_{xj} = y_{ij}]$$

The overall agreement rate for annotator i, denoted as  $R_i$ , is then:

$$R_i = \frac{1}{N_i} \sum_{j=1}^{N_i} r_{ij}$$

where  $y_{ij} \in \{A, B, T\}$  is the label assigned by annotator i to sample j. The label T (i.e., Tie) is treated as a distinct category, and it's agreement is counted only on exact matches.

Figure 9 illustrates the distribution of these agreement rates for our 69 annotators for SpeechJudge-Data (raw). The distribution is generally unimodal with a peak in the 60–70% range<sup>3</sup>, which indicates a consistent and reliable level of performance across the annotation pool.

#### INTELLIGIBILITY ANNOTATION ANALYSIS

We provide a detailed analysis of the relationship between the mostly common used objective intelligibility metric, Word Error Rate (WER), and the subjective human judgments of intelligibility. Our goal is to determine the extent to which WER can serve as a reliable proxy for human perception.

We use all the speech samples from SpeechJudge-Data (raw) for this analysis. We visualize the relationship between WER and the subjective text accuracy in Figure 10. For the regular speeches (the orange curve), we observe a consistent negative correlation: as the WER increases, its perceived text accuracy steadily declines. For the expressive speeches (the green curve), the similar trend holds

<sup>&</sup>lt;sup>3</sup>We have noted that one annotator's agreement with the others is less than 30%, so we ultimately removed his data from SpeechJudge-Data.

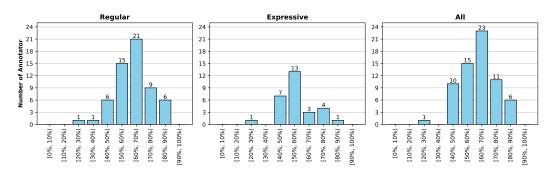


Figure 9: Distribution of individual annotator agreement rates. Most annotators fall between 50% and 80%, typically peaking in the 60–70% range.

for expressive speech when WER is under about 12%. When WER is over the threshold, however, the correlation between WER and the subjective text accuracy weakens significantly. We think this divergence is sourced from that the greater stylistic variations in expressive speech pose a substantial challenge to the robustness of ASR systems compared to the regular samples.

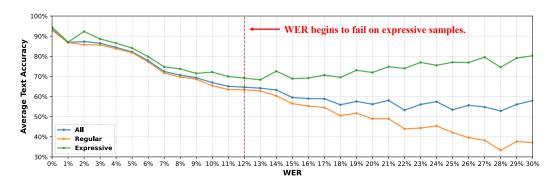


Figure 10: The relationship between the human-annotated text accuracy and WER.

# D DETAILS OF EVALUATION ON THE SPEECHJUDGE-EVAL BENCHMARK

During the evaluation on the SpeechJudge-Eval Benchmark of Table 2, we adopt the following protocol for each model:

- WER (Radford et al., 2023; Gao et al., 2023): We employ Whisper-large-v3<sup>4</sup> Radford et al. (2023) for English texts, and Paraformer-zh<sup>5</sup> Gao et al. (2022, 2023) for Chinese and code-switching texts.
- **SIM** (Chen et al., 2022): We compute the cosine similarity between the WavLM TDNN<sup>6</sup> Chen et al. (2022) speaker embeddings of generated samples and the prompt samples.
- FAD (Kilgour et al., 2019): We use the officially released checkpoint, VGGish, to obtain the FADs of audios.
- **DNSMOS** (Reddy et al., 2022): We use the officially released script<sup>7</sup> to calculate the DNSMOS of audios.

<sup>&</sup>lt;sup>4</sup>https://huggingface.co/openai/whisper-large-v3

<sup>&</sup>lt;sup>5</sup>https://huggingface.co/funasr/paraformer-zh

<sup>&</sup>lt;sup>6</sup>https://github.com/microsoft/UniSpeech/tree/main/downstreams/speaker\_verification

<sup>&</sup>lt;sup>7</sup>https://github.com/microsoft/DNS-Challenge/blob/master/DNSMOS/dnsmos\_local.py

- CE, CU, PC, and PQ (Tjandra et al., 2025): We use the officially released toolkit<sup>8</sup> to get the predicted MOS for audios.
- AASIST (Jung et al., 2022): It is a common baseline model for audio deepfake detection, employs a heterogeneity-aware approach to integrate spectral and temporal sub-graphs. We use a large-scale in-house corpus to train the model.
- ADV (Wang et al., 2025a): It is a state-of-the-art (SOTA) deepfake detection model built upon the pre-trained w2v-bert-2.09. It utilizes a multi-task training approach involving deepfake source tracing to extract robust audio deepfake features. We use the same corpus of AASIST to train the model.
- AudioLLMs: We use the plain prompt of Table 1 to instruct AudioLLMs to pairwise score the naturalness of two audios. For the closed-source models, we use the official API released by Google<sup>10</sup> for Gemini and OpenAI<sup>11</sup> for GPT. We use the model variants gemini-2.5-flash, gemini-2.5-pro, gpt-4o-mini-audio-preview-2024-12-17, and gpt-4o-audio-preview-2025-06-03 for Gemini-2.5-Flash, Gemini-2.5-Pro, GPT-4o mini Audio, and GPT-4o Audio.

#### E More Evaluation Results of Existing AudioLLMs

Using AudioLLM as a judge models, prompt engineering strategies are usually believed crucial for improving the performance (Zheng et al., 2023; Manakul et al., 2025). Some common prompt engineering strategies include using the CoT prompts to activate the model's thinking and reasoning abilities (Zhang et al., 2025a; Liu et al., 2025c; Manakul et al., 2025), or employing few-shot evaluation formats Zheng et al. (2023); Xiaomi (2025).

In this study, we investigate whether using the CoT from Table 1 helps AudioLLMs better judge speech naturalness. Interestingly, we find that some closed-source AudioLLMs, such as Gemini-2.5-Flash, improve their performance on SpeechJudge-Eval through this thinking and reasoning process. However, this strategy often does not work for existing open-source AudioLLMs. For example, the results in Table 5 show that while Gemini-2.5-Flash consistently improves with the CoT prompt, Kimi-Audio-7B-Instruct, which is already the best-performing open-source model on SpeechJudge-Eval (Table 2), actually sees a decline in performance when using the CoT prompt.

Table 5: Perf	formance of	AudioLLN	As on S	SpeechJu	ıdge-Eval	l when using	CoT	prompt.
							•	

Model	Regular	Expressive	Total
Kimi-Audio-7B-Instruct	65.5	68.0	67.0
w/ CoT prompt	67.4	66.1	66.5
Gemini-2.5-Flash	73.5	66.2	69.1
w/ CoT prompt	75.0	67.5	70.5

Based on our preliminary qualitative analysis, we believe the reason why the open-source AudioLLMs do not work well with the CoT prompt is that their foundational capabilities are relatively weak. These weaknesses include instruction-following (such as format-following), multiple-audio understanding, long-text generation, and reasoning abilities. This is also why, when we developed SpeechJudge-GRM, we did not directly apply RLVR on top of Qwen2.5-Omni-7B. Instead, we used an initial SFT stage as a cold start.

# F TRAINING DETAILS OF SPEECHJUDGE-GRM

**SFT Stage** We use Gemini-2.5-Flash (Comanici et al., 2025) to generate the CoT data for SpeechJudge-Data (train). For the total 42K samples, Gemini-2.5-Flash's judgments agree with

<sup>8</sup>https://github.com/facebookresearch/audiobox-aesthetics

<sup>&</sup>lt;sup>9</sup>https://huggingface.co/facebook/w2v-bert-2.0

<sup>&</sup>lt;sup>10</sup>https://ai.google.dev/gemini-api/docs/models

<sup>&</sup>lt;sup>11</sup>https://platform.openai.com/docs/models

Table 6: Post-training of Qwen2.5-0.5B-TTS based on SpeechJudge.

Model	Reg	ular	Articulatory		Code-switching		Cross-lingual		Expressive		Avg	
	WER	SIM	WER	SIM	WER	SIM	WER	SIM	WER	SIM	WER	SIM
Qwen2.5-0.5B-TTS	2.63	0.698	10.53	0.679	23.87	0.666	10.51	0.593	11.10	0.706	11.73	0.668
w/ INTP	2.06	0.697	8.62	0.694	18.37	0.663	7.12	0.588	9.80	0.708	9.19	0.670
w/ SpeechJudge-Data	2.12	0.698	8.92	0.678	19.01	0.657	7.72	0.583	9.97	0.707	9.55	0.664
w/ SpeechJudge-GRM (offline)	2.31	0.698	7.83	0.681	15.36	0.662	7.84	0.593	9.72	0.709	8.51	0.668
w/ SpeechJudge-GRM (online)	2.35	0.696	8.45	0.674	15.87	0.653	7.82	0.580	9.79	0.702	8.85	0.661

human feedback on 25K samples, while they disagree on 17K samples. During the SFT stage, we fine-tune Qwen2.5-Omni-7B (Thinker) (Xu et al., 2025) on the 25K CoT data using LoRA (Hu et al., 2022) with a rank of 128. We use Adam (Kingma & Ba, 2015; Loshchilov & Hutter, 2019) as the optimizer and set the learning rate to 5e-5. The maximum number of tokens per batch is 4000. We select the best checkpoint on SpeechJudge-Data (dev) as the SFT model, SpeechJudge-GRM (SFT).

**RL Stage** We use the 17K samples (as described above) to conduct DAPO (Yu et al., 2025), which is an enhanced variant of GRPO (Shao et al., 2024). We utilize the ms-swift<sup>12</sup> toolkit to launch the training process. We initialize the policy model with the SFT model and use LoRA training with a rank of 64. The number of rollouts for each prompt is set to 8, and the batch size is 32. The learning rate is 5e-6. We select the best checkpoint on SpeechJudge-Data (dev) as the final SpeechJudge-GRM model, i.e., SpeechJudge-GRM (SFT+RL).

# G SAMPLE SELECTION AND POST-TRAINING BASED ON SPEECHJUDGE-GRM

#### G.1 DETAILS OF SUBJECTIVE EVALUATION

During the construction of SpeechJudge-Data, we hired human labelers from a data crowdsourcing company. To verify the effectiveness of our training for them and to ensure the high quality of both the dataset and the resulting SpeechJudge-GRM, the human subjects for the final sample selection and TTS post-training experiments (Section 5.3 and 5.4) were all experienced speech generation researchers. All these researchers had extensive audio backgrounds, with a minimum of two years of experience in speech synthesis.

We randomly selected the subjective evaluation samples from both SeedTTS-Eval (Anastassiou et al., 2024)<sup>13</sup> and Amphion-TTS-Eval (Zhang et al., 2025b,c)<sup>14</sup>. The evaluation set for each system in Figure 6 consists of 70 samples, while the set for each system in Figure 5 contains 100 samples. Each audio sample in these evaluations received at least three independent ratings. These subjective evaluation results show that the annotation quality of SpeechJudge-Data largely aligns with the judgments of professional researchers.

#### G.2 OBJECTIVE RESULTS

We present the objective results (WER and SIM) of the Qwen2.5-0.5B-TTS post-training in Table 6. The results show that all four post-training methods significantly improve the WER. This trend is similar to the subjective intelligibility results shown in Figure 6a.

Regarding the SIM metric, both w/ INTP and w/ SpeechJudge-GRM (offline) either match or slightly outperform the baseline model, while the other two methods show a slight decline. However, the objective SIM results appear to be in slight conflict with the subjective speaker similarity results in Figure 6b. For instance, in the subjective evaluation, w/ INTP actually shows a decrease in speaker similarity (Win: 24.30%, Lose: 32.90%).

Through follow-up interviews with the subjects who participated in our subjective evaluation, we gathered additional qualitative insights. Participants consistently reported that the synthesized sam-

<sup>&</sup>lt;sup>12</sup>https://github.com/modelscope/ms-swift

<sup>&</sup>lt;sup>13</sup>https://github.com/BytedanceSpeech/seed-tts-eval

<sup>&</sup>lt;sup>14</sup>https://huggingface.co/datasets/amphion/Amphion-TTS-Eval

ples, both before and after post-training, demonstrated excellent speaker similarity, closely matching the reference speaker's timbre and style. In most cases, participants found it challenging to distinguish any significant differences in similarity, leading them to prefer selecting "Tie". For example, in Figure 6b, all four methods have the highest "Tie" proportion, each exceeding 40%. This demonstrates that post-training methods centered on naturalness (SpeechJudge-based) or intelligibility (INTP-based) are not yet fully aligned with speaker similarity, which requires further research into speaker similarity alignment.