THINK OUT LOUD, PAUSE IN SILENCE: CONFIDENCE-GUIDED REFLECT–PAUSE–ABORT FOR ROBUST AUDIO PERCEPTUAL UNDERSTANDING

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ABSTRACT

Large Audio Language Models (LALMs) mainly fail for two errors: perceptual errors misidentifying background sounds or speaker turns, and reasoning errors drifting rationales that decouple from acoustic evidence. To address these issues, we propose an adaptive framework that couples perceptual grounding with computation that expands only when needed. First, we introduce PAQA, a Perceptually grounded Audio QA dataset of 7,470 multiple-choice items that pairs multi-speaker, background-rich audio with stepwise reasoning and reflection annotations, enabling supervision of verifiable audio-grounded rationales. On the modeling side, we propose ConfAudio, which unifies explicit, reflective reasoning (fine-tuned on PAQA) with implicit, pause-driven latent computation trained via GRPO. A confidence-aware controller monitors lowest-group-confidence (LGC) during decoding to insert pauses when uncertainty rises and to abort unstable trajectories, thereby reallocating compute toward hard perceptual segments. To stabilize the training process, we design a composite reward that balances answer correctness, reasoning–answer consistency with perceptual robustness, and output format. Across PAQA, MMAU-mini, and MMAR, ConfAudio consistently improves both accuracy and consistency, particularly in noisy, multi-speaker conditions. Our results demonstrate that confidence-guided, adaptive reasoning—grounded in verifiable acoustic evidence—mitigates the dominant perceptual and reasoning failure modes in Audio-QA.

1 INTRODUCTION

Large language models (LLMs) have made notable progress in *reasoning* via chain-of-thought (CoT) prompting and reinforcement-learning (RL) post-training (Jaech et al., 2024; Guo et al., 2025), and similar advances have extended to visual modalities (Huang et al., 2025a; Feng et al., 2025). Unlike text, audio introduces unique challenges such as overlapping speakers, pronoun ambiguity, shifting emotions, and variable, noisy acoustic conditions. These factors often induce perceptual errors that are among the most prevalent failure modes of current models (Liu et al., 2024a).

Recent audio-capable LLMs (e.g., Qwen2-Audio (Chu et al., 2024), Audio Flamingo (Kong et al., 2024), SALMONN (Tang et al., 2023)) still tend to address audio question answering (Audio-QA) by mapping transcripts directly to answers, with limited verification against the underlying acoustic evidence. Prior audio CoT efforts (Zhang et al., 2024; Wang et al., 2024) supervise long free-form rationales but do not consistently yield improvements on challenging problems. Moreover, RL-only pipelines (Chen et al., 2024; Zhang et al., 2024; Xu et al., 2025; Zhou et al., 2025) improve answer accuracy, yet the explicit reasoning process itself has not shown consistent benefits for Audio-QA.

Previous work (Liu et al., 2024a) shows that dominant failures on the MMAR benchmark arise from perceptual errors and downstream reasoning mistakes. This underscores the need to first establish a strong perceptual foundation by explicitly incorporating verifiable evidence, especially in two high-frequency scenarios: (i) distinguishing environmental sounds, and (ii) accurately transcribing multi-speaker conditions. Importantly for audio reasoning, many acoustic cues (e.g., rhythmic density, timbre) cannot be faithfully translated into free-form text, so enforcing text-only rationales risks losing critical granularity. In real-world speech comprehension, humans often reflect on their reasoning process and, when uncertain, pause briefly to deliberate before responding. Inspired by

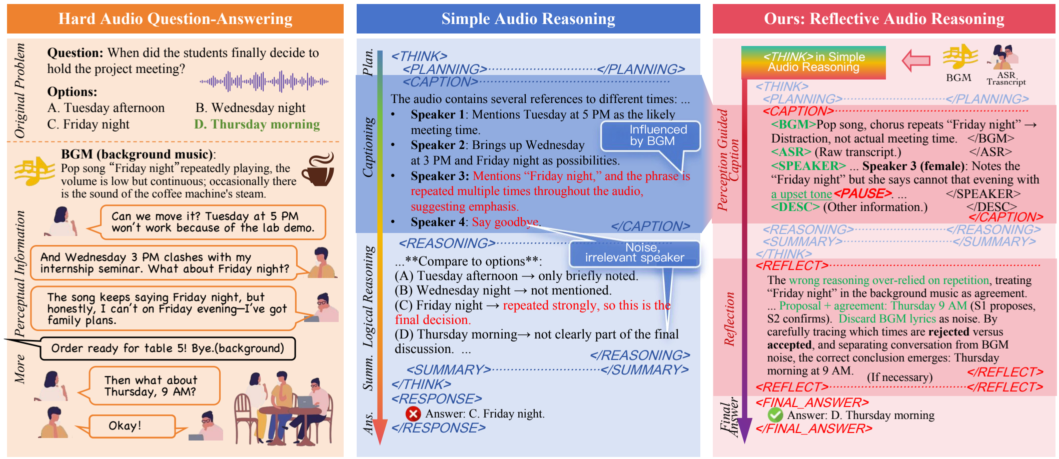

Hard Audio Question-Answering
Original Problem
Question: When did the students finally decide to hold the project meeting?
Options:
A. Tuesday afternoon
B. Wednesday night
C. Friday night
D. Thursday morning
BGM (background music):
Pop song "Friday night" repeatedly playing, the volume is low but continuous; occasionally there is the sound of the coffee machine's steam.
Perceptual Information
Can we move it? Tuesday at 5 PM won't work because of the lab demo.
And Wednesday 3 PM clashes with my internship seminar. What about Friday night?
The song keeps saying Friday night, but honestly, I can't on Friday evening—I've got family plans.
Order ready for table 5! Bye.(background)
More
Then what about Thursday, 9 AM?
Okay!
Simple Audio Reasoning
Plan.
Captioning
Logical Reasoning
Summ.
Ans.
<THINK>
<PLANNING>……</PLANNING>
<CAPTION>……
The audio contains several references to different times: ...
• Speaker 1: Mentions Tuesday at 5 PM as the likely meeting time.
• Speaker 2: Brings up Wednesday at 3 PM and Friday night as possibilities.
• Speaker 3: Mentions "Friday night," and the phrase is repeated multiple times throughout the audio, suggesting emphasis.
• Speaker 4: Say goodbye.
</CAPTION>
Influenced by BGM
Noise, irrelevant speaker
<REASONING>……
...**Compare to options**:
(A) Tuesday afternoon → only briefly noted.
(B) Wednesday night → not mentioned.
(C) Friday night → repeated strongly, so this is the final decision.
(D) Thursday morning→ not clearly part of the final discussion. ...
</REASONING>
<SUMMARY>……</SUMMARY>
</THINK>
<RESPONSE>
✗ Answer: C. Friday night.
</RESPONSE>
Ours: Reflective Audio Reasoning
<THINK> in Simple Audio Reasoning
BGM
ASR Trasncript
Perception Guided Caption
Reflection
Final Answer
<THINK>
<PLANNING>……</PLANNING>
<CAPTION>……
<BGM>Pop song, chorus repeats "Friday night" → Distraction, not actual meeting time. </BGM>
<ASR> (Raw transcript.) </ASR>
<SPEAKER> ... Speaker 3 (female): Notes the "Friday night" but she says cannot that evening with a upset tone<PAUSE>. ... </SPEAKER>
<DESC> (Other information.) </DESC>
</CAPTION>
<REASONING>……</REASONING>
<SUMMARY>……</SUMMARY>
</THINK>
<REFLECT>……
The wrong reasoning over-relied on repetition, treating "Friday night" in the background music as agreement. ... Proposal + agreement: Thursday 9 AM (S1 proposes, S2 confirms). Discard BGM lyrics as noise. By carefully tracing which times are rejected versus accepted, and separating conversation from BGM noise, the correct conclusion emerges: Thursday morning at 9 AM.
</REFLECT>
(If necessary)
<REFLECT>……</REFLECT>
<FINAL_ANSWER>
✓ Answer: D. Thursday morning
</FINAL_ANSWER>

Figure 1: A challenging audio QA case with **perceptual errors**. Repeated lyrics in the BGM and multi-speaker overlaps mislead simple reasoning. Although the **CAPTION** includes background sound and cues, the model reaches the correct answer after **REFLECT** reasoning which takes advantage of perceptual information. In particular, when enough acoustic features are encountered, the decoder emits a special **PAUSE** token to allocate additional latent compute.

these observations, we pose the central research question: *Can an audio–language model be endowed with adaptive deep reasoning, combining perceptually grounded and verifiable CoT with pause-driven latent computation, to robustly overcome audio perceptual errors?*

Interference from background sound and disambiguating multiple speakers are central challenges in real-world audio understanding, yet they remain underrepresented in existing datasets. To address this gap, we construct **PAQA**, the first **P**erceptually grounded **A**udio **QA** dataset, coupling multi-speaker, background-rich audio with stepwise reasoning and reflection annotations. PAQA contains 7,470 multiple-choice Audio-QA pairs. Each example provides structured annotations—including background-music separation, speaker analysis, and multi-turn reflections—and records both an internal answer and a final response. As illustrated in Fig. 1, a model with simple reasoning incorrectly selects "Friday night" due to overreliance on repeated mentions, failing to distinguish background sound from actual conversation. In contrast, a model equipped with reflective reasoning isolates background sound and irrelevant speakers and aligns evidence to arrive at the correct answer.

To handle non-textualizable acoustic signals, we propose **ConfAudio**, an adaptive reasoning framework that unifies explicit reflective reasoning with implicit latent computation. Explicit reasoning is realized through fine-tuning on our curated dataset, while implicit reasoning is enabled by a learned `<pause>` token trained with Group Relative Policy Optimization (GRPO). A confidence-aware module monitors the lowest group confidence (LGC) during decoding and adaptively inserts a pause token when confidence falls below a threshold; it also aborts unstable trajectories to ensure stability. This mechanism encourages the model to attend more deeply to acoustic evidence and to re-segment speakers when necessary. In addition, we design a composite reward that jointly balances answer correctness, reasoning consistency, and output format. We evaluate ConfAudio on the test sets of PAQA, MMAU-mini, and MMAR, where it consistently outperforms strong baselines.

(1) We construct **PAQA**, the first dataset that integrates multi-speaker and background-rich audio with stepwise reasoning and reflection annotations. It covers multi-speaker QA, noisy speech-to-text translation, and environment-centric QA, encouraging models to ground decisions in acoustic evidence rather than transcript shortcuts.

(2) We propose **ConfAudio**, an adaptive reasoning framework that combines explicit audio-grounded reflective reasoning with implicit latent computation. The latter is realized through a learned pause token triggered by a lowest group confidence (LGC) score, enabling the model to silently allocate additional computation when uncertain or abort unstable trajectories.

(3) We design a composite reward that jointly optimizes answer accuracy, format compliance, acoustic consistency, and length control, discouraging unnecessary verbosity. Experiments demonstrate that ConfAudio enhances adaptive reasoning, effectively reducing perceptual and reasoning errors.

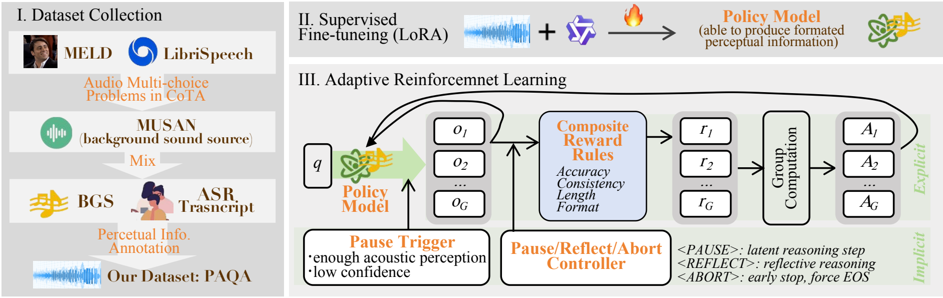

I. Dataset Collection
MELD
LibriSpeech
Audio Multi-choice Problems in CoTA
MUSAN (background sound source)
Mix
BGS
ASR Trasncript
Percetual Info. Annotation
Our Dataset: PAQA
II. Supervised Fine-tuneing (LoRA)
Policy Model
(able to produce formated perceptual information)
III. Adaptive Reinforcemnet Learning
q
Policy Model
o_1
o_2
o_G
Composite Reward Rules
Accuracy
Consistency
Length
Format
r_1
r_2
r_G
Group Computation
A_1
A_2
A_G
Explicit
Pause Trigger
·enough acoustic perception
·low confidence
Pause/Reflect/Abort Controller
<PAUSE>: latent reasoning step
<REFLECT>: reflective reasoning
<ABORT>: early stop, force EOS
Implicit

Figure 2: An overview of our work.

2 Data Collection for Complex Audio Understanding

2.1 Complex Audio Understanding

R1-AQA (Chen et al., 2024) and Omni-R1 (Zhou et al., 2025) show that requiring the model to read *write out* step by step text does not guarantee improvements in audio QA (AQA). In several AQA settings, explicit CoT provides only marginal or no gains over answer-only decoding, sometimes even increasing latency. For simple ASR or S2TT tasks, we also observed that models tend to overfit surface transcripts rather than perform robust reasoning over acoustic evidence (see Fig. 6). Unlike text-only scenarios, real-world audio understanding requires grounding in acoustic cues (e.g. speaker turns, overlapping speech regions) and careful attention to scene components. Motivated by this, we further analyze Qwen2-Audio's bad cases on the CoTA (Zhang et al., 2024) benchmark and identify two major challenges:

- difficulties in handling multi-speaker conversations, where insufficient speaker diarization under overlapping or interleaved turns leads to incorrect attribution of utterances and a consequent loss of dialogue coherence;
- failures in environmental-sound discrimination, whereby non-speech events and nonsignificant background sound are classified as evidence;

To advance speaker-aware modeling and noise-resilient perception, we construct a dataset that integrates multi-speaker and background-rich audio with stepwise reasoning and reflection annotations.

Background-rich augmentation. We sample background audio from publicly licensed environmental categories in MUSAN (Snyder et al., 2015) (e.g. alarms, typing, rain, cafeteria, street traffic, soft instrumental music). For a clean speech clip s and a background clip n, we first RMS-normalize both and then scale the background so that the power ratio satisfies $\mathrm{SNR}_{\mathrm{dB}} = 10$, ensuring that the speech remains ten times stronger than the background, audibly present but not dominant. Each item is annotated with a tag indicating the presence and type of background (e.g., 'Soft instrumental music – please ignore.'), which discourages unnecessary reliance on background cues.

Multi-speaker Alignment. To discourage models from shortcutting on global transcripts and to encourage speaker-localized reasoning, we annotate turn structures in a `<SPEAKER>` section using a compact, ordered format such as **"Speaker 1: ..."**. We then apply Qwen3-ASR (Team, 2025) to each audio sample to generate a verbatim raw transcript. To mitigate hallucination and drift between summaries and verbatim text, we introduce a quote-presence test (QPT), which measures fuzzy overlap between `<ASR>` snippets $A = a_i$ and `<SPEAKER>` sentences $S = s_i$. Specifically, SeqRatio is defined as the standard difflib ratio on normalized strings. Items with $QPT < 0.85$ are flagged for revision. The formulation is given by:

$$\mathrm{QPT} = \frac{1}{M} \sum_{i=1}^{M} \max_{1 \le j \le N} \mathrm{SeqRatio}\big(\mathrm{norm}(s_i),\, \mathrm{norm}(a_j)\big).$$

2.2 Reflection to correct wrong initial responses

In natural conversation, speakers frequently self-monitor and revise their utterances. Building on prior work showing that reflection-driven self-correction improves model performance in reasoning tasks (Shinn et al., 2023; Madaan et al., 2023; Wang et al., 2023), we adopt a reflection-augmented pipeline for complex audio understanding. Concretely, a lightweight baseline model first generates an initial <RESPONSE> for each audio-QA item, as illustrated in the third column of Fig. 1. We then automatically detect errors—such as option mismatches, speaker attribution mistakes, hallucinated content inconsistent with ASR transcripts, or misinterpretation of noise cues—and prompt the model to produce a grounded diagnostic analysis <REFLECT>. This analysis explicitly references <BGM>, <SPEAKER>, and <ASR> to explain the failure and localize the supporting evidence. Conditioned on this analysis, the model is guided to generate a corrected <FINAL_ANSWER>. For training, we store the triplet (<RESPONSE>, <REFLECT>, <FINAL_ANSWER>), which provides explicit reflection supervision and, from each original audio item, yields an additional corrected example, effectively doubling the supervised data while enriching them with interpretable, perception, grounded self-correction signals.

The dataset supports a range of tasks, including multi-speaker QA, speech-to-text translation under noise, and environment-centric QA. An in-depth analysis of the final PAQA dataset is provided in Appendix A, while a detailed statistical overview is summarized in Table 1.

Table 1: Dataset Source and Statistics.

Dataset Source	Main Skills Learning	BGS Used	Quantity	Reflection
Multi-Speaker (Zhang et al., 2024)	Multi-speaker Speech QA	Free Sound	1.5k	1.4k
MELD (Poria et al., 2019)	Speech Emotion QA	Sound Bible	1.5k	1.4k
CoVoST2 (Wang et al., 2020)	Speech-to-Text Translation	No	1.5k	No

3 METHODOLOGY

3.1 ADAPTIVE REASONING WITH CONFIDENCE

In real-world speech comprehension, humans often reflect on their reasoning process and, when uncertain, pause briefly to deliberate before responding. This dual mechanism of explicit explanation and implicit contemplation is especially critical in complex conversational environments, where overlapping speakers, ambiguous references, and noisy conditions demand both transparent justification and adaptive internal reflection. To address this challenge, we introduce Adaptive Reasoning With Confidence (ARC). ARC integrates two complementary mechanisms: explicit control, which filters and aborts unreliable trajectories, and implicit control, which enables pause-based latent computation. A comparison with alternative methods is presented in Fig. 3.

3.1.1 LOWEST GROUP CONFIDENCE (LGC)

We consider the lowest group confidence to provide sufficient signals for estimating trace quality. Given an input x and completion tokens $\mathbf{y} = (y_1, \ldots, y_T)$ with per-token log-probabilities $\ell_t = \log P_\theta(y_t \mid x, y_{<t})$, we segment the sequence into overlapping windows $\mathcal{W}k$ of length w with stride s. For each window, we compute a normalized geometric mean probability

$$C_k = \exp\left(\frac{\sum t \in \mathcal{W}k m_t \, \ell_t}{\sum t \in \mathcal{W}k m_t + \delta}\right),$$

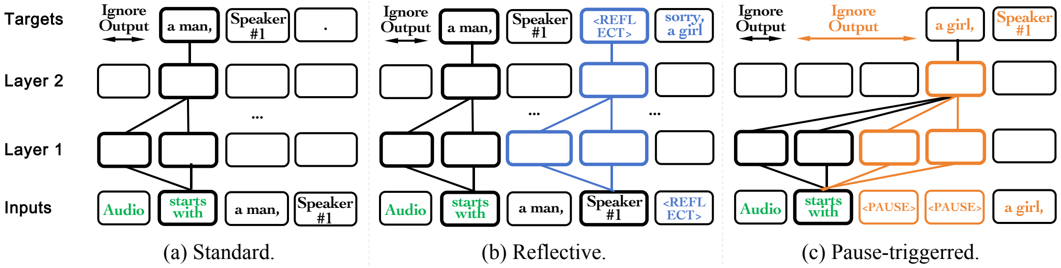
where $m_t \in \{0, 1\}$ masks out prompt or padding tokens, and δ avoids division by zero. The lowest-group-confidence of the trajectory is then

$$\mathrm{LGC}(\mathbf{y}) = \min_{k=1,\ldots,K} C_k$$

This definition emphasizes the weakest local segment: a small cluster of highly uncertain tokens is sufficient to reduce LGC, making it a sensitive indicator of local reasoning collapse, which has been justified effectively according to Wang et al. (2025).

3.1.2 EXPLICIT CONTROL: REFLECTIVE REASONING

After supervised fine-tuning, we explicitly encourage the model to output a dedicated <REFLECT> segment following its initial chain-of-thought reasoning. For each prompt with G sampled generations, the model produces a transparent reflection that can be inspected and analyzed.



(a) Standard. (b) Reflective. (c) Pause-triggerred.

Figure 3: Standard vs. reflective-inference vs. pause-inference (and finetuning). Similar to Goyal et al. (2024), the rounded squares denote one Transformer operation (a self-attention and MLP) in a 2-layer Transformer. Any Ignore Output denotes that during inference, the corresponding output token is not extracted and thus, not fed back autoregressively.

3.1.3 IMPLICIT CONTROL: PAUSE-BASED LATENT THINKING

Beyond explicit rejection, we allocate hidden compute via *implicit* pauses. Let $\tau_{\text{pause}} > \tau_{\text{abort}}$ be a softer threshold. At each step t, we choose an action:

$$\text{action}(t) = \begin{cases} \text{abort} & \text{if } C_{k(t)} < \tau_{\text{abort}}, \\ \text{pause} & \text{if } \tau_{\text{abort}} \le C_{k(t)} < \tau_{\text{pause}}, \\ \text{continue} & \text{otherwise.} \end{cases} \tag{1}$$

When a pause is triggered at $t^\star$, the model emits <PAUSE> and generates up to K_{p} latent tokens $\hat{\mathbf{z}}_{1:L}$ (with $L \le K_{\text{p}}$) that are *not* surfaced in the visible output but update the hidden state for subsequent decoding, with $\oplus$ means concatenation of tokens:

$$\tilde{\mathbf{y}} = \mathbf{y}_{1:t^\star} \oplus \texttt{<PAUSE>} \oplus \hat{\mathbf{z}}_{1:L}, \qquad \mathbf{y}_{\text{vis}} = \mathbf{y}_{1:t^\star}. \tag{2}$$

To bias pausing precisely when text references speech-only, non-textual cues (where extra acoustic reasoning is beneficial), we maintain a keyword set, such as "tone", "pitch", whenever any $w \in \mathcal{A}$ appears in the recent context, we add a positive logit bias $\beta_{\text{ac}} > 0$ to the <PAUSE> token:

$$\ell_{\texttt{<PAUSE>}} \leftarrow \ell_{\texttt{<PAUSE>}} + \beta_{\text{ac}} \cdot \mathbb{I}\big[\exists\, w \in \mathcal{A} \text{ in context}\big]. \tag{3}$$

Crucially, the same confidence signal $\{C_k\}$ that defines $\text{LGC}(\mathbf{y}) = \min_k C_k$ during training also governs the runtime policy above (pause vs. continue vs. abort). This shared mechanism ties sample selection (via top-p filtering on LGC) to inference-time latent compute allocation (via <PAUSE> triggers) and safety (via abort), yielding a coherent control scheme.

3.2 REWARD FUNCTION

We propose a novel composite reward function that integrates semantic accuracy with structural validity prior to policy optimization, ensuring that models not only produce correct answers but also generate interpretable reasoning. Formally, the overall reward is defined as the sum of three components: accuracy reward, consistency reward, and format reward. The accuracy reward measures whether the predicted answer matches the ground-truth label while also accounting for reasoning coherence and explanation quality:

$$R_{\text{acc}} = w_{\text{ans}}\, \mathbf{1}[\hat{y} = y] + w_{\text{cons}}\, \text{Cons}(\hat{y}, \hat{y}_{\text{reason}}) + w_{\text{len}}\, \text{LenScore}(L), \tag{4}$$

where $\text{Cons}(\hat{y}, \hat{y}\text{reason})$ measures the consistency between the final answer and the intermediate reasoning, and $\text{LenScore}(L)$ discourages both under- and over-elaboration. The format reward validates whether the output follows the required structured reasoning schema; it is assigned 1.0 if all required tags are present, correctly ordered, and properly nested, and 0.0 otherwise. Specifically, the consistency measure discourages spurious reliance on background sound (BGS), enforces alignment between speaker summaries and ASR evidence, and ensures that the internally declared answer matches the final emitted answer. The format reward is denoted as $r\text{fmt}(x) \in 0, 1$.

Let a completion be denoted by x. We parse both <FINAL_ANSWER> (FA) and <RESPONSE> (R), taking FA as the primary channel and falling back to R when FA is absent. From x, we extract a predicted letter $\hat{y}_L(x) \in \{A, B, C, D\}$ and a channel text $\hat{y}_T(x)$, defined as the raw inner text of FA or R. Within <THINK>, let $\mathcal{A} = a_j$ denote ASR sentences and $\mathcal{S} = s_i$ denote speaker snippets (i.e., quoted spans or colon-delimited clauses).

3.2.1 Consistency Reward.

Beyond task accuracy and format concerns, we regularize chains for *internal consistency* along three axes: (i) **BGS robustness** blocks spurious causal use of background sound; (ii) **Speaker–ASR fidelity** rewards quotes/snippets that appear in the ASR transcript; and (iii) **Reasoning–Answer consistency** rewards agreement between the last internal choice from <THINK> and the final answer. Let $r_{\text{bgs}}(x) \in \{0, 1\}$, $r_{\text{spk}}(x) \in [0, 1]$, and $r_{\text{ra}}(x) = \mathbf{1}\big[\tilde{y}_L(x) = \hat{y}_L(x)\big] \in \{0, 1\}$. We combine them with a hard BGS gate and a convex mixture:

$$\mathcal{R}_{\text{cons}}(x) = r_{\text{bgs}}(x)\left(\lambda_{\text{spk}}\ r_{\text{spk}}(x)\ +\ \lambda_{\text{ra}}\ r_{\text{ra}}(x)\right), \quad \lambda_{\text{spk}}, \lambda_{\text{ra}} \geq 0,\ \lambda_{\text{spk}} + \lambda_{\text{ra}} = 1. \tag{5}$$

In words, any offending BGS causal claim zeroes the consistency reward; otherwise, we interpolate between sentence-level Speaker–ASR alignment and self-agreement of the final answer. The default weights $\lambda_{\text{spk}} = \lambda_{\text{ra}} = 0.5$ worked well in our runs.

BGS robustness. To prevent spurious cues from background sound, we penalize any reasoning/description sentence that *uses BGS as causal evidence*. Let $S(x)$ be sentences from <THINK>:<REASONING> and <DESCRIPTION>. Let $\mathcal{B}$ be a lexicon of BGS terms (e.g., "bgm", "background sound", instrument names), $\mathcal{C}$ causal connectives (e.g., "because/therefore"), and $\mathcal{N}$ negations/hedges (e.g., "ignore"). We set $r_{\text{bgs}}(x) = 0$, otherwise $r_{\text{bgs}}(x) = 1$:

$$r_{\text{bgs}}(x) = \begin{cases} 0, & \text{if reasoning invokes BGS as causal evidence,} \\ 1, & \text{otherwise.} \end{cases} \tag{6}$$

Speaker–ASR fidelity We softly align speaker snippets to ASR sentences using a normalized similarity $\text{sim}(\cdot,\cdot) \in [0, 1]$ and average each snippet's best match:

$$r_{\text{spk}}(x) = \frac{1}{|\mathcal{S}|} \sum_{s_i \in \mathcal{S}} \max_{a_j \in \mathcal{A}} \text{sim}\big(\text{norm}(s_i),\ \text{norm}(a_j)\big) \in [0, 1]. \tag{7}$$

This penalizes fabricated quotes while tolerating minor lexical or punctuation variations, where sim as a normalized edit similarity (token- or character-level):

$$\text{sim}(u, v) = 1 - \frac{\text{Lev}\big(u,\ v\big)}{\max\{|u|,\ |v|\}} \ \in [0, 1], \tag{8}$$

where $\text{Lev}(\cdot,\cdot)$ is the Levenshtein edit distance and $|\cdot|$ denotes sequence length.

Reasoning–Answer consistency. In long, noisy chains, decoding drift can make the model "reason to A but output C". Therefore, we design rewarding self-agreement. From <THINK> we extract the last declared option $\tilde{y}_L(x)$. Let $\hat{y}_L(x)$ denote the final emitted letter (FA/R). Then we calculate $r_{\text{cons}}(x) = \mathbf{1}\big[\tilde{y}_L(x) = \hat{y}_L(x)\big]$.

3.2.2 Length shaping When Accurate.

To encourage adequate evidence gathering (speaker attribution, noise filtering) without overlong chains, we introduce a length sub-reward when the accuracy reward is 1. Let $T(x)$ be a simple token proxy (count of non-whitespace sequences in the *whole* completion). With thresholds $T_{\min} = 300$, $T_{\max} = 600$, and decay scale $K > 0$, we use a piecewise-linear schedule:

$$r_{\text{len}}(x) = \begin{cases} \frac{T(x)}{T_{\min}}, & 0 \leq T(x) < T_{\min}, \\ 1, & T_{\min} \leq T(x) \leq T_{\max}, \\ \max\big(0,\ 1 - \frac{T(x) - T_{\max}}{K}\big), & T(x) > T_{\max}. \end{cases} \tag{9}$$

To enforce clean outputs, we gate by the absence of post-answer content, where any non-whitespace after </FINAL_ANSWER> leads to 0.

3.3 Reinforcement Learning Training

Training proceeds in two phases:

(1) Supervised fine-tuning (SFT). We minimize $\mathcal{L}_{\text{SFT}}$ on *deep-thinking* data (with a small mixture of external audio-CoT when available) under grammar masking and scheduled exposure to τ_{p}.

(2) Group-aware Relative Policy Optimization(GRPO). Starting from the SFT checkpoint (reference policy π_{ref} frozen), we generate groupwise rollouts, compute $R(\mathbf{z})$ via Eq. equation 4, and update π_θ with GRPO.

We partition rollouts by task group $g \in \{\text{PAQA}, \text{AVQA}\}$ and difficulty bucket (low/med/high). Within each group, we compute groupwise baselines to reduce variance:

$$\tilde{R}^{(i)} = R^{(i)} - \frac{1}{m_g} \sum_{j \in g} R^{(j)}.$$

Let $A^{(i)} = \tilde{R}^{(i)}$ be the advantage. We optimize a clipped PPO objective over tokens t:

$$\mathcal{L}_{\text{GRPO}}(\theta) = -\mathbb{E}\Big[\min\Big(\rho_t^{(i)} A^{(i)},\ \text{clip}\big(\rho_t^{(i)}, 1-\epsilon, 1+\epsilon\big) A^{(i)}\Big)\Big], \quad \rho_t^{(i)} = \frac{\pi_\theta(z_t^{(i)}|\cdot)}{\pi_{\theta_{\text{old}}}(z_t^{(i)}|\cdot)}.$$

We incorporate confidence into Group Relative Policy Optimization (GRPO) by using the lowest-group-confidence (LGC) as a sample weight. For a trajectory i with task reward r_i^{task} (covering correctness, formatting, consistency, and length penalties) and group baseline $\bar{r}$, the advantage is calculated as

$$A_i = w_i\,(r_i^{\text{task}} - \bar{r}),$$

where w_i is a clipped, standardized function of the trajectory's LGC, and $w_i = 0$ for filtered samples. The final reward may also include recovery and leak terms when pause control is enabled:

$$r_i = r_i^{\text{task}} + \eta \cdot \max(0, \text{LGC}^{\text{post}} - \text{LGC}^{\text{pre}}) - \lambda_{\text{leak}} \cdot \mathbf{1}\{\text{leak}\},$$

where η, λ_{leak} are selected to balance accuracy, formatting, and robustness.

4 Experiments

4.1 Experimental Setup

All methods fine-tune the same pretrained backbone (Qwen2-Audio-7B-Instruct). The training is conducted on the Chen et al. (2024) framework. To train our models, we use a node with 2 H200 GPUs (282GB). The batch size per GPU is 1, with gradient accumulation steps of 2 for a batch size of 16. We use a learning rate of $1e-6$, a temperature of 1.0, 8 responses per GRPO step, and a KL coefficient β of 0.1. For pause latent thinking mechanism with entropy-based triggering, we set tau_pause_quantile=0.50 that allows up to 8 pauses per sequence with 64 thinking tokens each, plus recovery bonus (0.05) and leak penalty (1.0) for think token containment. We evaluate six configurations: **SFT**, which uses supervised fine-tuning only with no reasoning schema and no `<pause>`; **RL-NoThink**, GRPO post-training that emits answers directly without `<REFLECT>` or `<pause>`; **RL-ExpCoT**, GRPO with explicit `<THINK>` (including `<REFLECT>`) but no `<pause>`; **Ours (ConfAudio)**, GRPO combining the explicit schema and `<pause>`; and **External** baselines comprising Audio-Reasoner, Audio-Thinker, and R1-AQA. We use PAQA (8k question-answering pairs) for supervised finetuning; and use 30,000 data from AQVA for Reinforcement learning. We do evaluation on **PAQA Test**(hard), **MMAU-mini**, and **MMAR**, the results are listed below.

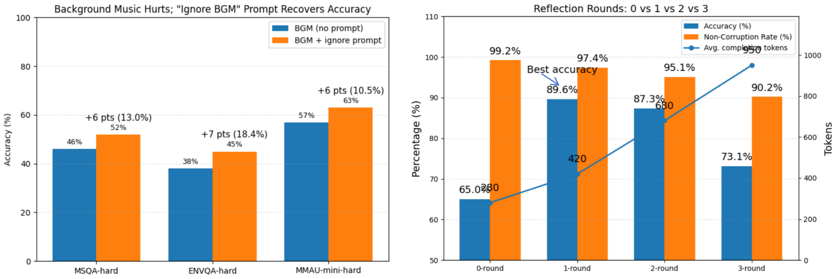
4.2 Main Results

Table 2 summarizes the main results across two aggregated benchmarks (MMAU-mini, MMAR). **SFT. vs. Baseline** Injecting perceptual information via SFT is useful, especially for the speech setting that we primarily target. However, because our fine-tuning data is speech-heavy, domain shift appears in music.

RL better than SFT. GRPO-NoThink performs better than SFT, and each module in our model improves the effectiveness well. This demonstrates that optimizing structured reasoning and perceptual-consistency signals is essential to enhance audio perceptual reasoning.

Table 2: Performance on MMAU Test-mini and MMAR (higher is better).

Method	MMAU Test-mini				MMAR			
	Sound	Music	Speech	Average	Sound	Music	Speech	Average
Qwen2-Audio	61.26	53.59	48.05	54.30	33.33	24.27	32.31	30.00
SFT	62.76	44.61	55.86	54.41	41.82	34.95	45.92	40.90
GRPO-NoThink	68.17	61.38	60.66	63.40	51.52	38.83	45.92	45.40
GRPO+CoT	70.27	59.88	59.46	63.20	**58.18**	33.98	46.60	46.30
GRPO+ExpCoT	75.07	58.98	63.66	65.90	44.85	39.81	59.86	48.20
- weak format	72.97	61.08	63.96	66.00	42.42	43.69	61.22	49.10
Ours (ConfAudio)	**75.67**	**62.27**	**64.26**	**67.40**	**58.18**	**45.63**	**62.59**	**55.50**
Audio-CoT	62.16	55.99	56.16	58.10	35.76	25.24	34.01	31.67
Audio-Reasoner	60.06	64.30	60.70	61.71	43.64	33.50	32.99	36.71



(a) Background Music Hurts. "Ignore BGM" Prompt Recovers Accuracy.

(b) Reflection Rounds Trade-off. One-turn reflection is enough.

Figure 4: Comparison between different audio situations. In (b), lower corruption rate is better.

Pause mechanism works. In final results, Ours(Exp+Imp) surpasses all other baselines. Especially, MMAU-Music +3.29 and MMAR-Music +5.82 indicate that pause-driven latent thinking also helps in music/complex acoustic scenarios. Though more stable during training, introducing pause-based latent tokens increases training time, raising max_pause_token from 1 to 3 roughly doubles training time. See more details in Fig.8.

Abort mechanism balances speed with formatting penalties. While abort (early stopping under high uncertainty/high entropy) improves throughput and latency control, we observe that it tends to output think-only simplified content, yielding very low format rewards. We therefore down-weight the format reward and make a baseline with a weak format reward, and ConfAudio still outperforms, suggesting abort mainly trades speed/stability, whereas pause is the primary driver of performance.

4.3 Ablation Study

As shown in Fig.4(a), the added background sound measurably degrades zero-shot performance, while explicit “ignore BGS” cues and our reflection step (Section 3) substantially improve accuracy. In Fig.4(b), we compare different turns of reflection, moving from 0 to 1 reflection round yields a large accuracy jump while keeping outputs mostly clean. However, adding more rounds brings diminishing returns and “overthinking”. Moreover, excessive pausing hurts performance(see Fig. 5), then setting max pause token as 1-3 is suitable. We also evaluate on the test set of PAQA(see Tab.3), on the category of multi-speaker and MELD, ConfAudio performs the best. When we set the background sound with SNR=5dB, it greatly influences the effect of models, but ConfAudio deteriorates the least, retaining state-of-the-art accuracy and consistency due to its pause-driven implicit reasoning and BGM-aware rewards.

4.4 More Observations.

Overall, the RL training progressed well, but there is a clear collapse around 200 steps. The trigger was the length-reward design: during exploration, longer completions earned higher scores, but once a response exceeded 600 tokens a linear decay penalty kicked in. The policy reacted by abruptly shortening completions to 200 tokens; these outputs were often incomplete, so the format reward dropped to 0 and the accuracy reward fell to 0.5. After this shock, training recovered and stabilized, indicating the policy adapted to the length constraint(See Fig.8).

Model	Multi-Speaker(hard)		BGS-rich	
	Acc.	Consistency ↑	Acc.	@SNR=5dB ↑
Qwen2-Audio	42.2	38.5	41.0	20.1
SFT	46.2	41.5	44.0	31.2
GRPO-NoThink	52.7	48.3	50.2	38.4
GRPO-ExpCoT	61.5	58.7	60.8	47.6
Ours	**70.4**	**68.1**	**69.5**	**57.8**
Audio-CoT	50.6	46.9	48.3	35.0
Audio-Reasoner	56.8	52.7	55.9	41.8

Table 3: Evaluation on the test set of PAQA.

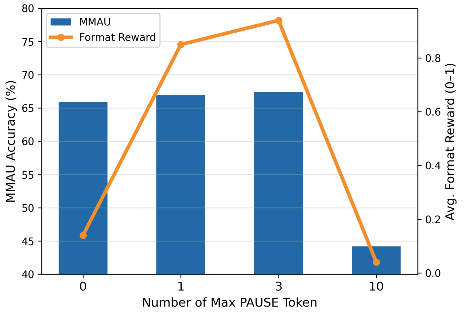


Figure 5: Abaltion study of #<PAUSE> tokens. Set max pause token as 1-3 is suitable.

5 Related Works

5.1 Large Audio–Language Models (LALMs)

Early LALMs such as Qwen2-Audio(Chu et al., 2024), Audio Flamingo(Kong et al., 2024), and SALMONN(Tang et al., 2023) advanced ASR, but remained fragile in real-world reasoning tasks involving overlapping speakers and non-stationary noise. On-demand CoT in Audio Flamingo 3(Chen et al., 2025) and structured CoT in Audio-Reasoner (Zhang et al., 2024)—yet models often reverted to transcript shortcuts whenever acoustic evidence was difficult to verbalize. To address these limitations, we release a structured dataset that couples multi-speaker and background-rich audio, explicitly guiding LALMs to ground decisions in acoustic rather than purely textual evidence.

5.2 Reasoning in (Audio-)Language Models: Explicit and Reflective

In LLMs, structured reasoning through CoT, reflection, and RL post-training has yielded consistent gains beyond supervised fine-tuning (SFT) (Guo et al., 2025; Kimi Team, 2025). Replication, robustness, and efficiency studies further refined these pipelines, while Vision-R1 and Video-R1 extended RL-based reasoning to perceptual tasks with overthinking suppression (Yu et al., 2025; Huang et al., 2025a;b; Feng et al., 2025). In audio, GRPO-style RL underlies R1-AQA and Omni-R1 (Shao et al., 2024; Chen et al., 2024; Zhou et al., 2025), with mixed evidence on whether RL alone suffices. More recent approaches (Liu et al., 2024b; Xu et al., 2025; Li et al., 2025; Jin et al., 2025) highlight that objectives should reward useful and concise reasoning rather than verbosity. In this work, we instead unify explicit, audio-grounded reasoning with reflection, operationalized through a multi-term reward that enforces correctness, grounding, and conciseness.

5.3 Implicit Reasoning and Pause-Gated Latent Compute

Complementary to explicit rationales, implicit computation allocates additional internal processing before token emission. Learned <pause> tokens can trigger silent forward passes (Goyal et al., 2023), echoing earlier adaptive-computation approaches(Graves, 2016; Banino et al., 2021)that learn instance-dependent halting policies. To our knowledge, such latent computation has not been systematically validated in audio–language reasoning. Our contribution is to extend <pause> to LALMs and couple it with a lowest-group-confidence (LGC) controller: when confidence drops on acoustically inexpressible cues, ConfAudio diverts into a short, budgeted latent stream and can abort tail trajectories under severe uncertainty.

6 Conclusion

In this paper, to address two entangled failure modes in Audio-QA, perceptual and reasoning errors, we build **PAQA** (7,470 items) to supervise verifiable, audio-grounded rationales, and propose **ConfAudio**, which couples explicit reflection with implicit, pause-driven latent thinking trained via GRPO with a composite reward. Specially, a lowest-group-confidence controller inserts <pause> or aborts unstable trajectories. ConfAudio delivers consistent gains in accuracy and consistency under noisy, multi-speaker conditions, narrowing the gap between acoustic evidence and reasoning.

Ethical considerations.

Our dataset is constructed from publicly available corpora or controlled augmentations, with all speech either anonymized or synthesized to avoid privacy leakage. Despite the contributions, several limitations remain. First, while our dataset is carefully annotated with multi-speaker and background-rich reasoning structures, its scale is modest compared to general-purpose audio corpora, which may limit coverage of rare conversational phenomena.

Reproductivity Statement.

We prioritize reproducibility by releasing dataset specifications, and preprocessing scripts for background injection, speaker segmentation, and ASR alignment. All training configurations—including optimizer settings, batch sizes, learning rate schedules, and LoRA ranks—are documented and released as YAML files. Our evaluation follows a consistent protocol across our dataset, MMAU, and MMAR, reporting accuracy, consistency, and robustness under noise. Results are averaged over multiple random seeds to avoid cherry-picking. Upon publication, we will release our training data, code, inference pipelines, and checkpoints under an open-source license.

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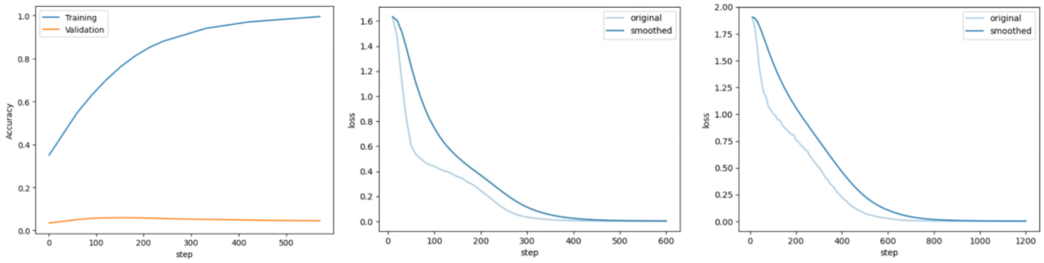


(a) Overfitting on Simple Translation Tasks of CoT fine-tuned model.

(b) Training loss on ASR of CoT fine-tuned model.

Figure 6: The training dynamics of a chain-of-thought (CoT) fine-tuned model (Qwen2-Audio-7B), indicating the model overfits to the training set in simple translation tasks. This suggests that CoT fine-tuning without additional regularization or more diverse data fails to yield robust generalization, particularly for tasks requiring broader reasoning beyond surface transcript matching.

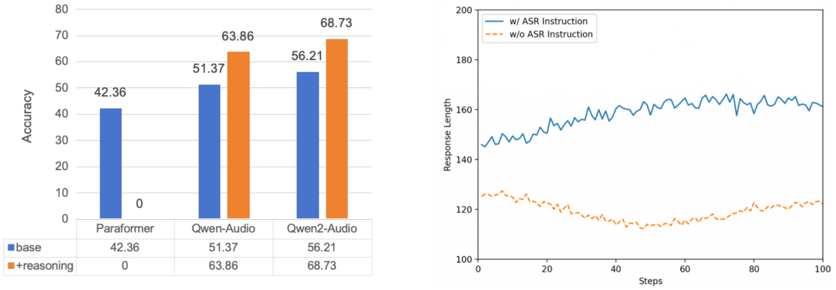
A Data Collection and Exploration of Hard Audio Understanding

A.1 Limitations of Simple ASR-Centric Text Reasoning

Early approaches to audio reasoning typically relied on converting speech into text via automatic speech recognition (ASR) and then performing reasoning over the textual transcript. While effective to some extent, this paradigm inevitably discards information that is uniquely embedded in the audio signal itself. To probe the limitations of this pipeline, we first evaluated the ASR+text reasoning approach on benchmarks such as CoVoST2 and MMAU. In CoVoST2, model performance is largely determined by raw ASR accuracy, and we observed that "simple ASR" signals are quickly memorized without yielding robust generalization. A case study is shown in Fig.9, which highlights several intrinsic challenges. Homophones and proper-name ambiguities necessitate long-range semantic modeling and external knowledge retrieval, while gendered pronouns in Chinese (e.g., "he/she") lack reliable acoustic cues and thus require contextual inference for disambiguation. In particular, Paraformer's frame-level alignment, coupled with strong language model priors, tends to induce a "nearest-neighbor copying" effect—yielding high accuracy on in-distribution transcripts but exhibiting pronounced failures under distributional shifts. Moreover, exposure to translation-oriented data (e.g., CoVoST2) can bias models such as Qwen-Audio to mistakenly trigger translation behavior, sometimes converting Chinese speech into other languages when acoustic cues are uncertain.

As shown in Fig.7(a), there is an improvement on base models if we asked them to answer questions with thinking in the format of `<THINK>...</THINK><FINAL_ANSWER>...</FINAL_ANSWER>`. Therefore, we collected 2,050 samples from a subset of CoVoST2 (including 50 challenging cases reserved for the test set) and employed Kimi to generate chain-of-thought style annotations. Using this data, we fine-tuned Qwen2-Audio and Qwen-Audio and evaluated them on the designated test set. However, the models exhibited severe overfitting(see Fig.6(b)) after only a single epoch of training: while the outputs consistently followed the required `<THINK>...</THINK><FINAL_ANSWER>...</FINAL_ANSWER>` format and the training loss rapidly approached zero, the test accuracy dropped below 5%. This observation indicates that the gradients primarily optimized for surface-level grapheme mapping and fixed output formatting, without fostering genuine cross-sentence reasoning, coreference resolution, or knowledge-grounded inference.

Consequently, these observations indicate that the "Thinking" component of chain-of-thought supervision should be allocated primarily to more challenging audio understanding tasks, such as multi-speaker dialogues and noisy environments—where reasoning signals genuinely drive the model to overcome semantic ambiguities and enforce knowledge-aware interpretations, rather than merely replicating templates on simple ASR tasks.



(a) the comparison of base model and model with reasoning prompt.

(b) the comparison of prompt with or without ASR finetuned on MSQA.

Figure 7: Experiments on the Exploration of Good Audio Reasoning prompt.

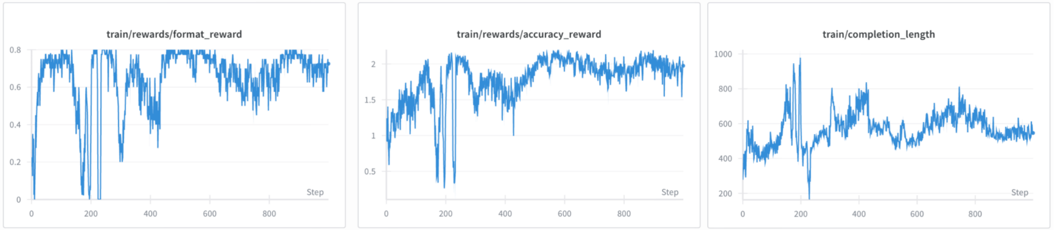


Figure 8: GRPO Training. Overall, the RL training progressed well, but there is a clear collapse around 200 steps. The trigger was the length-reward design: during exploration, longer completions earned higher scores, but once a response exceeded 600 tokens, a linear decay penalty kicked in. The policy reacted by abruptly shortening completions to 200 tokens; these outputs were often incomplete, so the format reward dropped to 0, and the accuracy reward fell to 0.5. After this shock, training recovered and stabilized, indicating the policy adapted to the length constraint.

A.2 Harder Audio Reasoning Tasks

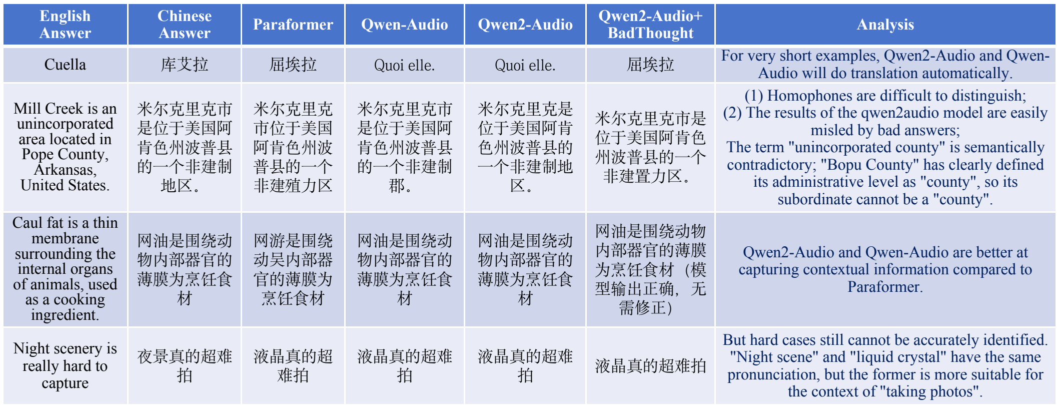
Following this, we further analyzed erroneous predictions of Qwen2-Audio on the MMAU benchmark. As shown in Fig.7(b), we compared fine-tuning trajectories on the MSQA dataset with and without ASR-augmented data. The results reveal that models trained with ASR supervision exhibit substantially longer response lengths, which we interpret as a proxy for deeper and more structured reasoning ability. This finding suggests that integrating ASR data into training not only improves transcription accuracy but also enhances the reasoning capacity of audio-language models. Therefore, in the first stage of fine-tuning, we deliberately incorporated the ASR-enriched data described in the previous section to further consolidate the model's ASR capability as a foundation for downstream reasoning.

Moreover, we processed the audio with MUSAN(Snyder et al., 2015), which satisfies target 10 dB SNR, according to

$$\mathrm{SNRdB} = 10 \log 10 \left(\frac{P_s}{P_{n,\mathrm{scaled}}} \right) = 10.$$

Let $P_s = \frac{1}{T} \sum_t s_t^2$ and $P_n = \frac{1}{T} \sum_t n_t^2$. The background gain is

$$k = \sqrt{\frac{P_s}{P_n \cdot 10^{\mathrm{SNR}_{\mathrm{dB}}/10}}} = \sqrt{\frac{P_s}{P_n \cdot 10}}.$$



English Answer	Chinese Answer	Paraformer	Qwen-Audio	Qwen2-Audio	Qwen2-Audio+ BadThought	Analysis
Cuella	库艾拉	屈埃拉	Quoi elle.	Quoi elle.	屈埃拉	For very short examples, Qwen2-Audio and Qwen-Audio will do translation automatically.
Mill Creek is an unincorporated area located in Pope County, Arkansas, United States.	米尔克里克市是位于美国阿肯色州波普县的一个非建制地区。	米尔克里克市位于美国阿肯色州波普县的一个非建殖力区	米尔克里克市是位于美国阿肯色州波普县的一个非建制郡。	米尔克里克是位于美国阿肯色州波普县的一个非建制地区。	米尔克里克市是位于美国阿肯色州波普县的一个非建置力区。	(1) Homophones are difficult to distinguish; (2) The results of the qwen2audio model are easily misled by bad answers; The term "unincorporated county" is semantically contradictory; "Bopu County" has clearly defined its administrative level as "county", so its subordinate cannot be a "county".
Caul fat is a thin membrane surrounding the internal organs of animals, used as a cooking ingredient.	网油是围绕动物内部器官的薄膜为烹饪食材	网游是围绕动旲内部器官的薄膜为烹饪食材	网油是围绕动物内部器官的薄膜为烹饪食材	网油是围绕动物内部器官的薄膜为烹饪食材	网油是围绕动物内部器官的薄膜为烹饪食材（模型输出正确，无需修正）	Qwen2-Audio and Qwen-Audio are better at capturing contextual information compared to Paraformer.
Night scenery is really hard to capture	夜景真的超难拍	液晶真的超难拍	液晶真的超难拍	液晶真的超难拍	液晶真的超难拍	But hard cases still cannot be accurately identified. "Night scene" and "liquid crystal" have the same pronunciation, but the former is more suitable for the context of "taking photos".

Figure 9: Bad cases of Paraformer, Qwen-Audio and Qwen2-Audio on the simple ASR task.

B Case Study

Bad Case A

<THINK>
<PLANNING>
The user's question is: Based on the conversation, what are the speakers trying to assemble? I need to analyze the dialogue between the speakers to identify the item they are constructing. The audio provides the audio clip, and I should analyze it for details related to the assembly activity. </PLANNING>
<CAPTION>
The audio features a conversation among three individuals in what sounds like a workspace. They are discussing an instruction manual and the assembly process. - Speaker 1: Expresses frustration with the instruction manual, stating that it's difficult to distinguish pieces A and B.
- Speaker 2: Proposes that piece B has a slightly beveled edge, but concedes that it's similar.
- Speaker 3: Agrees that it looks like Bevel Edge and expresses hope that it's correct.
- Speaker 1: States it is Bevel Edge B, and declares they can complete the assembly.
- Speaker 2: Hope is right and doesn't want to misassemble again.
- Speaker 1: Confirms it is Bevel Edge B and asks everyone to take deep breaths and move on.

The core task is assembling an item where they are currently putting together parts, such as bevel edges.
</CAPTION>
<REASONING>
1. Analyzing the Dialogue: The dialogue revolves around distinguishing parts (A and B) and confirming a beveled edge.
2. Identifying the Assembly Activity: The key element is Bevel Edge, suggesting the speakers are assembling something with beveled sides.
3. Evaluating Options: - (a) A table: While a table might require beveling, the central focus isn't just about assembling a table. - (b) A chair: Similarly, a chair might require beveling, but it isn't their primary focus. - (c) A bed: A bed typically features beveled edges, aligning perfectly with the conversation. This is the most likely scenario. - (d) A bookshelf: A bookshelf is less likely to have beveled edges.
4. Concluding the Item: Based on the bevel edges and the distinct focus on distinguishing them, it can be inferred that the speakers are assembling a bed. </REASONING>
<SUMMARY>
The speakers are differentiated by focusing on the Bevel Edge assembly of a bed. By eliminating other less relevant options through reasoning, the final conclusion is that they are assembling a bed. </SUMMARY>
</THINK>

Observed failure. Original CoT concludes bed from generic cues—"piece A vs. B," "bevel(ed) edge," "don't misassemble"—none of which uniquely identify a bed. This is a classic *reasoning overreach*: drawing a strong category conclusion from evidence that is common to many flat-pack builds. No category-specific anchor terms (e.g., *headboard, shelf, tabletop, backrest*) appear in the dialogue.

Here is the reflection of this case.

Reflection of Bad Case A

<REFLECT> Evidence available from the dialogue is generic to many flat-pack builds: “piece A vs. B,” “bevel(ed) edge,” “don’t misassemble,” and “let’s move on.” No category-specific anchors are heard (e.g., for a bed: headboard/footboard/rails/slats; for a bookshelf: shelf/upright/back panel/bracket; for a table: tabletop/apron; for a chair: backrest/seat/armrest). Given absent anchors, the safest policy is to avoid over-commitment. If forced to choose among the four, “bookshelf” is the most compatible with beveled front edges on shelves and frequent A/B part distinctions during shelf panel assembly. Confidence remains low; with an “uncertain” option, I would state insufficient evidence. </REFLECT>
<ANSWER>Bookshelf.</ANSWER>

C Prompt Template

A Sample Case of Our PAQA Data

<THINK>
<PLANNING>
The user wants to understand the dynamic changes ...... </PLANNING>
<CAPTION>
<BGM>Street noise; intermittent car horns.</BGM>
<SPEAKER>A: adult F; B: adult M; alternating turns.</SPEAKER>
<ASR></ASR>
<DESCRIPTION>The audio clip predominantly features static noise. ...... similar to that of a detuned television or a device failing to receive a signal.</DESCRIPTION>
</CAPTION>
<REASONING>
1. Identify changes in Intensity (Volume): ...... struggling to maintain a consistent output, adding to the impression of something malfunctioning or broken. </REASONING>
<SUMMARY>
The static noise in the audio is highly dynamic. ... leading to a sense of disorder and instability. </SUMMARY>
</THINK>
<RESPONSE>
The audio presents a static noise, ... is one of energetic chaos, preventing any possibility of calm or predictability. </RESPONSE>

<REFLECT1> Does ”A” mention the cake, not B? Check turn 3.</REFLECT1>
<NEW_RESPONSE>A</NEW_RESPONSE>
<REFLECT2> Does ”A” mention the cake, not B? Check turn 3.</REFLECT2>
<NEW_RESPONSE>B</NEW_RESPONSE>

Prompt template of Refelection Sample

After producing the <RESPONSE>, you must perform a structured self-reflection step.
1. Compare the <RESPONSE> with the overall task requirements and check for issues such as: - Missing or incomplete coverage of the audio content (did it stop too early? were some speakers/segments missed?). - Repetition or redundant phrasing that should be removed or marked clearly. - Speaker attribution or diarization errors (wrong speaker assignment, merged speakers, or split speakers). - Prosody/tone/intonation mistakes or overemphasis on irrelevant details. - Inconsistent reasoning or labels (final choice must align with the reasoning and context). - Overly simplistic or single-hypothesis reasoning when alternatives exist.
2. Inside <REFLECT>...</REFLECT>, explicitly list: - The problems found in <RESPONSE>. - The corrections or adjustments needed (without referencing or leaking the gold standard answer text). - Any uncertainties or low-confidence areas.
3. Then rewrite the improved answer inside <FINAL_ANSWER>...</FINAL_ANSWER>, ensuring: - All necessary content is covered. - No hallucinated details are added beyond the given <CAPTION>, <ASR>, and <DESCRIPTION>. - Speaker attributions and reasoning are consistent. - The final answer matches the reasoning and is labeled correctly with confidence if required.
Format strictly as: <REFLECT> [Your structured reflection here] </REFLECT>
<FINAL_ANSWER> [Your corrected, high-quality final answer here] </FINAL_ANSWER>
Here is the original bad answer: Turn0 Here is the golden answer: Golden_Ans

D The Use of Large Language Models (LLMs)

In order to reduce typos during the writing process and to optimize complex sentence structures so that the article becomes simpler and easier to read, we use mainstream large language models to refine certain paragraphs. For example, we use prompts such as “Help me correct the typos and grammatical errors in the above text, and streamline the logic to make it clear and easy to understand.”