Multi-Task Instruction Tuning via Data Scheduling for Low-Resource Arabic SpeechLLMs

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Abstract

Audio large language models (LLMs) enable unified speech understanding and generation, but adapting them to linguistically complex and dialect-rich settings such as Arabic–English remains challenging. We present a controlled study of multi-task instruction tuning for an Arabic-centric audio LLM across generative tasks including ASR and speech and text summarization, and discriminative tasks including dialect and emotion recognition, in a resource-constrained setting. To support end-to-end Arabic speech summarization, we introduce **AraMega-SSum**, a *first* speech summarization resource for training and benchmarking Arabic-centric AudioLLMs. We compare four training strategies *(i) Uniform Mixing (UM)*, *(ii) Task-Progressive Curriculum (TPC)*, *(iii) Aligner-Based Diverse Sampling (ADS)* for training-time batch construction, and *(iv)* A two-stage *TPC→ADS* strategy. Our results show a clear *task-dependent trade-off*: TPC and uniform mixing favor generative tasks, while ADS is strongest for SER. The two-stage *TPC→ADS* strategy achieves the best DID performance across both backbones while preserving competitive generative quality. The adapted models also outperform zero-shot proprietary baselines, including Gemini-2.5-Pro, on discriminative tasks. We made **AraMega-SSum** and all experimental resources available to the community.[1]

1 Introduction

Large language models (LLMs) are rapidly evolving into native multimodal systems capable of unified speech understanding and generation (Xu et al., 2025a). However, adapting these "omni" models to linguistically complex and low-resource settings such as the Arabic–English bilingual space remains challenging. This setting combines dialectal variation, code-switching, and paralinguistic cues such as emotion, which are often difficult for general-purpose audio backbones to model effectively. Instruction tuning for this setting should jointly handle *generative* tasks such as ASR and summarization, and *discriminative* tasks such as dialect and emotion recognition. In practice, this is further complicated by severe imbalance across tasks and labels. Large ASR corpora can dominate optimization, while smaller paralinguistic datasets and minority classes may remain under-trained, resulting in negative transfer and reduced robustness (Chen et al., 2024).

We study how **data scheduling** and **within-batch task mixing** affect transfer, training stability, and final performance. *Data scheduling* controls how tasks and examples are sampled over training time, whereas *within-batch mixing* controls which tasks, labels, and acoustic conditions co-occur in the same batch.

Our main experiments use **Qwen2.5-Omni-7B** (Xu et al., 2025a), a dense open-weight omni model and our primary Arabic-centric adaptation target. We additionally include **Gemma-4-E4B-it**[2] as a secondary contrastive model to test whether the observed scheduling trends persist under a different architecture with stronger Arabic priors, including prior Arabic ASR exposure. Thus, Qwen captures the low-resource Arabic adaptation setting, while Gemma serves as an architecture sensitivity check.

To support end-to-end Arabic speech summarization, we introduce **AraMega-SSum**, a *first* Arabic speech summarization dataset for training and benchmarking Arabic-centric AudioLLMs. It contains 49,995 training samples and 4,000 test samples, corresponding to 222 and 16.98 hours of speech, respectively. The dataset is built from MSA-translated summaries and speaker-conditioned synthesized speech from 47 speakers across 10 Arab countries. A subset of the data

[1] AraMega-SSum

[2] https://huggingface.co/google/gemma-4-E4B-it

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is human-evaluated. AraMega-SSum is used only for summarization, while ASR, dialect identification, and emotion recognition are evaluated on real-speech benchmarks.

We instruction-tune Qwen2.5-Omni-7B and Gemma-4-E4B-it with LoRA and compare four training strategies. *(i)* **Uniform Mixing (UM)** is the standard baseline, sampling uniformly from the pooled multi-task data. *(ii)* **Task-Progressive Curriculum (TPC)** introduces tasks gradually, moving from lower-level acoustic objectives to higher-level objectives. *(iii)* **Aligner-Based Diverse Sampling (ADS)** preserves task proportions, balances labels for classification tasks, and *promotes cluster diversity* in the **aligner embedding space** that maps speech encoder representations to the LLM. *(iv)* **TPC→ADS** combines early-stage curriculum stabilization with later diversity-oriented training.

Our contributions are the following:

- We provide a controlled and comparative study of scheduling and batch composition for Arabic-centric omni audio instruction tuning across Generative tasks: *ASR and summarization*, and Discriminative tasks: *dialect identification, and emotion recognition*.
- We introduce **AraMega-SSum**, a novel and first dataset for Arabic speech summarization, with human evaluation on a subset of the dataset.
- We show that training schedules affect tasks differently: **TPC** favors generative performance, while **TPC→ADS** consistently achieves the best DID results across both backbones. Mixed SER results further show that diversity-oriented sampling is task-dependent rather than universally beneficial.

To the best of our knowledge, this is the *first* work to study specialized training strategies for an **Arabic-centric omni-model** spanning acoustic, linguistic, and paralinguistic tasks. It is also the *first* study to show how diversity in aligner embeddings can guide training-time batch construction while promoting task balance, label balance, and acoustic diversity. We emphasize that our contribution is not generic multi-task data mixing, but a controlled study of how task scheduling and batch construction affect Arabic-centric AudioLLM adaptation under limited resource.

Our findings reveal a task-dependent trade-off across training schedules, with some variation across model families. For **Qwen2.5-Omni-7B**, TPC achieves the best ASR performance and matches UM on summarization, suggesting that curriculum ordering helps preserve strong generative performance. For **Gemma-4-E4B-it**, UM gives the best ASR performance, while TPC performs best on summarization, indicating greater sensitivity to the choice of training schedule. The discriminative tasks exhibit a different pattern: TPC→ADS consistently achieves the best DID performance for both backbones, whereas standalone ADS gives the best SER results. Overall, **TPC** and **UM** are strongest for generative tasks, while diversity-oriented sampling provides task-specific gains on discriminative tasks, with **TPC→ADS** particularly effective for dialect identification.

2 Methodology

In Figure 1, we present an overview of the proposed methodology. We study data scheduling and within-batch task mixing for adapting an omni audio LLM to Arabic-centric speech understanding. We utilized the *Qwen2.5-Omni-7B* and *Gemma-4-E4B-it* architecture. For Qwen2.5-Omni-7B combines a Whisper-v3 audio encoder (Radford et al., 2023) with a 7B transformer decoder. A linear projection layer, called the **aligner**, maps encoder features into the LLM embedding space. We did the same for Gemma-4-E4B-it with USM-style audio encoder (Zhang et al., 2023b).

2.1 Tasks Formalization

We instruction-tune the model on a unified task, $\mathcal{T} = \{\mathcal{T}_g, \mathcal{T}_c\}$, set that includes generative ($\mathcal{G}$) tasks and classification ($\mathcal{C}$) tasks. Each training example consists of an audio input x (or a transcript for text-only summarization), a task prompt p, and a target output sequence y. We optimize the negative log-likelihood of the target tokens using cross-entropy.

Generative ($\mathcal{G}$) tasks. We include automatic speech recognition (ASR), text summarization (TSUM) given the transcript, and speech summarization (SSUM) given the speech input. For TSUM and SSUM, the target is a short summary in Arabic or English depending on the prompt.

Classification ($\mathcal{C}$) tasks. We include dialect identification (DID) and speech emotion recognition (SER). We formulate classification in the same instruction format by predicting a canonical label, so the loss remains token-level cross-entropy.

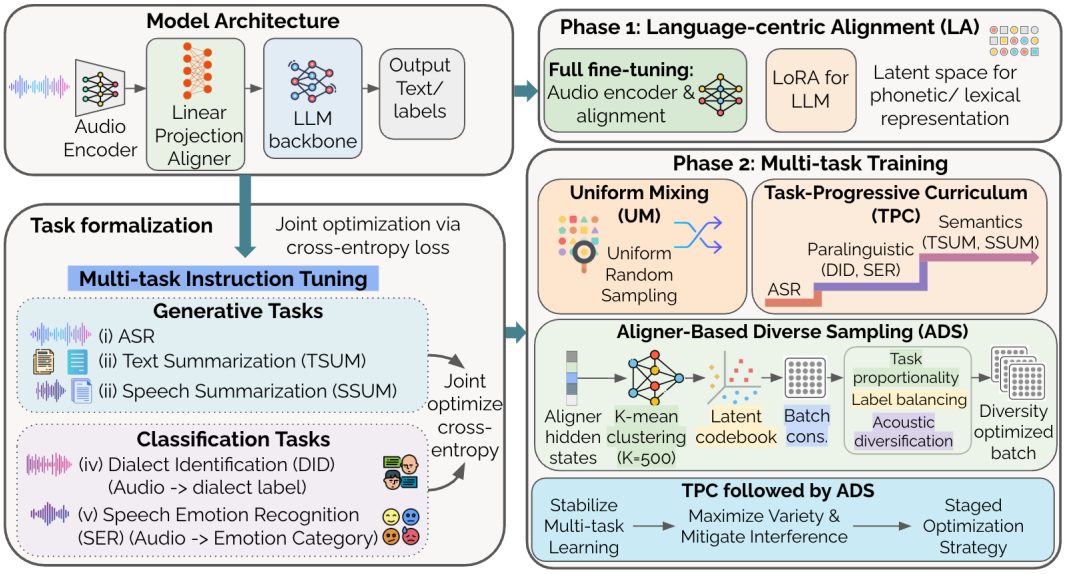


Figure 1: Overview of the proposed methodology. The framework adapts two AudioLLM backbones for a unified set of generative and classification audio tasks. The Qwen-based model uses a Whisper-v3 audio encoder with a Qwen2.5-7B LLM backbone, while the Gemma-based model uses a USM-style encoder with a Gemma-4 LLM backbone. Training proceeds in two stages: language-centric alignment (Phase 1), followed by multi-task adaptation (Phase 2), where we compare UM, TPC, ADS, and the two-stage TPC→ADS strategy.

2.2 Two-phase Adaptation

We use two training phases to separate modality alignment from multi-task scheduling effects.

Phase 1: Language-centric alignment. We fine-tune the audio encoder and aligner on large-scale bilingual ASR to align the audio representation with Arabic and English phonetic and lexical structure. During this phase, the LLM is adapted using LoRA.

Phase 2: Multi-task instruction tuning. We freeze the audio encoder and the aligner, and we update only the LoRA parameters in the LLM. All scheduling strategies in this phase use the same compute budget, meaning the same total number of training steps, so differences are attributable to the sampling strategy.

2.3 Data Scheduling and Batch Construction

In this section, we compare four strategies under the same model, optimization settings, and fixed computational setup.

A. Uniform Mixing Baseline (UM): We sample training instances uniformly from the pooled multi-task set $\mathcal{D}$. This is a standard baseline for instruction tuning.

B. Task-Progressive Curriculum (TPC): TPC trains in different stages ordered by task abstraction. The model is exposed to tasks in five sequential stages: **Acoustic**: ASR → **Paralinguistic**: DID, SER → **Semantic abstraction**: TSUM, SSUM. At each stage, we retain a fixed fraction of data from earlier stages to reduce forgetting.

Algorithm 1 ADS batch construction

$h_i \leftarrow A_\phi(x_i)$ for all $x_i \in \mathcal{D}$
$\mathcal{C} \leftarrow \mathrm{KMeans}(\{h_i\}, K = 500)$
Assign each x_i to nearest centroid $c_k \in \mathcal{C}$
while training **do**
  $\mathcal{B} \leftarrow \emptyset$
  for each task $t \in \mathcal{T}$ **do**
    $n_t \leftarrow M \cdot \mathrm{PriorDist}(t)$
    for each label $l \in \mathrm{UniqueLabels}(t)$ **do**
      $\mathcal{S}_{t,l} \leftarrow \{x_i : \tau_i = t,\ l_i = l\}$
      Sample $x \sim \mathcal{S}_{t,l}$ by round-robin over clusters
      $\mathcal{B} \leftarrow \mathcal{B} \cup \mathrm{UpsampleMinor}(x)$
    end for
  end for
  yield $\mathcal{B}$
end while

C. Aligner-Based Diverse Sampling (ADS): To mitigate task interference and label imbalance, particularly the dominance of MSA over regional dialects such as Gulf Arabic, we propose the ADS method, presented in Algorithm 1. The method promotes batch diversity by sampling from a discretized latent space obtained through K-means clustering of the aligner's output representations.

Latent representation. We first define a representation space using the hidden states of the linear aligner, A_ϕ. Given that the aligner bridges the acoustic encoder and the LLM, its embeddings capture the specific phonetic-semantic features rel-

evant for downstream semantic understanding. To minimize computational overhead, we perform clustering on a 3% random subset (≈77K utterances) of the training corpus. For each sample i, we extract the aligner hidden states and apply max-pooling over the temporal dimension to obtain a fixed-size vector $h_i \in \mathbb{R}^d$. We then apply K-Means clustering to generate a global acoustic-semantic codebook $\mathcal{C}$ with $K = 500$ centroids.

Batch construction and upsampling. During the SFT phase, each "effective batch" $\mathcal{B}$ is constructed to satisfy three constraints:

1. *Task proportionality:* The relative frequency of tasks in batch $\mathcal{B}$ follows the original distribution of the dataset to maintain stable convergence on high-volume tasks like ASR.
2. *Label balancing:* For discriminative tasks (e.g., Emotion, Dialect), we upsample minority classes ($UpsampleMinor(.)$) using smoothed inverse-frequency weights, moving the label distribution within each task toward balance.
3. *Acoustic diversification:* Samples are selected using a Round-Robin traversal across the K clusters within each task-label pair. This ensures that the model is exposed to a maximally diverse set of speakers and acoustic environments in every gradient update.

D. TPC followed by ADS: We also evaluate a two-stage training strategy that runs TPC for an initial portion of training to stabilize the shared representation, then switches to ADS for the remaining steps to emphasize label coverage and cluster diversity. This strategy uses the same total number of steps as the other strategies.

3 Datasets

To facilitate our language-centric alignment and multi-task training objectives, we curate training and evaluation data covering MSA, multiple Arabic dialects, and English. The development of Arabic-centric audio LLMs is challenging due to dataset scarcity. Large-scale ASR data are relatively available, whereas high-level spoken understanding and paralinguistic tasks remain limited and often exhibit strong label imbalance. A major gap is Arabic end-to-end speech summarization, for which paired speech and abstractive summaries are scarce in the public domain. AraMega-SSum is the only newly developed semi-synthetic dataset in our study, introduced to support this missing Arabic speech summarization setting. The remaining datasets for ASR, emotion recognition, and dialect identification are curated from public real-speech benchmarks.

3.1 AraMega-SSum

To address current gaps in the literature, we introduce and publicly release **AraMega-SSum**, a large-scale Arabic speech summarization dataset with 49,995 training samples (222 hours) and 4,000 test samples (16.98 hours). AraMega-SSum (Arabic Short Speech Summarization) serves as the first end-to-end dataset for semantic *understanding* directly from Arabic audio, providing a foundation for evaluating high-level generative understanding in Arabic-centric multimodal systems. A key contribution is the dataset's scale and quality for Arabic spoken short summarization. Given the extreme scarcity of paired audio-to-summary data in Arabic, we construct AraMega-SSum using a semi-synthetic pipeline that preserves semantic consistency while maximizing acoustic diversity. Our goal is to provide a large dataset that enables reproducible Arabic speech summarization evaluation, together with quality controls that reduce noise.

Translation. We leverage the **MegaSSUM** corpus (Matsuura et al., 2024) as our source, a large-scale English sentence-wise speech summarisation dataset based on the Gigaword dataset, comprising more than 3.8 million synthesized speech, transcription, and summary triplets. English speech is generated using a multi-speaker text-to-speech model trained on LibriTTS-R to produce natural-sounding utterances from the first sentences of news articles paired with their headlines, enabling broad coverage and consistent speech-text alignment. We translated the English source transcripts and their corresponding human-written summaries into MSA using *Gemini-2.5-flash*.

Translation Quality. To ensure the naturalness of the translations, we utilise GPT-4.1 as judge to evaluate the quality of translations with respect to *semantic equivalence*, *information preservation*, *contextual accuracy*, *completeness*, and *coherence*. The prompt is provided in Appendix Figure 8. Appendix Table 4 reports LLM-as-a-judge scores on a 1--10 scale. Moreover, we also performed a human evaluation to validate the translation quality. Table 5 shows a *similar pattern* based on ***human evaluation*** of a subset of 200 pairs. Under our cur-

rent setup and rubric, most outputs are fluent and semantically aligned with the source.

Audio Synthesis via Neural Voice Cloning. To reconstruct the speech modality, we use **XTTS-v2** (Casanova et al., 2024), a state-of-the-art multi-speaker latent diffusion model for speech synthesis. To reduce the risk of overfitting to static synthetic acoustic profiles, we leverage the model's zero-shot **voice cloning** capability. We use reference speaker audio from *MenaSpeechBank* (Ali et al., 2026) and extract speaker embeddings from **47 distinct speakers** representing **10 Arab countries**. This geographic breadth of the speakers audios helps ensure that the generated speech captures a wide range of regional prosody, pitch variation, and glottal characteristics across the Arab world. For each reference speaker, we maintain at least 10 high-quality voice clips, and randomly sample one reference clip to increase intra-speaker acoustic variability. This approach provides the necessary acoustic diversity for the LLM to generalize across heterogeneous recording conditions. The resulting dataset, **AraMega-SSum**, contains ≈**50K** pairs and provides a strong foundation for learning semantic representation.

Audio Quality. We validated the generated speech using both human assessment and standard automatic quality metrics. Three paid annotators rated 100 randomly sampled test-set clips for *naturalness*, *audio quality*, and *intelligibility* (Ju et al., 2024; Du et al., 2025). The clips achieved average scores of 3.98, 4.37, and 3.69 out of 5, respectively, with substantial-to-near-perfect annotator agreement (78.9 to 95.0) measured by Gwet's AC1 (Gwet, 2008) (Appendix Table 6). Complementary metrics show that the generated speech is generally intelligible and preserves speaker characteristics: Fanar Aura ASR obtains a WER of 15.5, NISQA gives an overall score of 3.95 out of 5 and speaker cosine similarity with the reference speakers is 0.66. To check that findings do not depend on synthetic speech, we also re-record 250 test items with native speakers: summarization scores on real and synthetic audio differ by at most 0.5 BERTScore points for all evaluated models (Appendix B.3).

3.2 Training Datasets

Datasets for language-centric alignment. For the model alignment experiments, we curate a high-quality ASR dataset of ≈**12K hours** from multiple sources, as shown in Table 1. We select these sources to ensure balanced linguistic coverage while maintaining computational efficiency. To improve acoustic robustness under real-world variability, we apply a targeted data augmentation strategy. Specifically, we apply **speed perturbation** (with factors of 0.9× and 1.1×), together with **additive noise augmentation** using the MUSAN (Snyder et al., 2015) and RIR (Ko et al., 2017) corpora on a subset. This process yields an additional ≈15,000 hours of synthetic high-variance audio. The final dataset consists of ≈**27K hours**.

Obj.	Task	Data	Total
		Phase 1: Language-centric Alignment	
ASR	ASR	QASR (Mubarak et al., 2021), MASC (Al-Fetyani et al., 2023), MGB-3/5 (Ali et al., 2017, 2019), GigaSpeech (Chen et al., 2021), GALE,[1] TED-LIUM 3 (Hernandez et al., 2018), LibriSpeech (Panayotov et al., 2015), CV (ar/en) (Ardila et al., 2020), SPGISpeech (O'Neill et al., 2021), + in-house	12,000h
ASR	ASR	Augmentation	≈15,000h
Total			**≈27,000h**
		Phase 2: Multi-task Training	
Gen.	ASR	6.44% subset of Phase 1	≈1,740h
Gen.	SSUM	MegaSSUM (Matsuura et al., 2024) + AraMega-SSum (ours)	374h
Gen.	TSUM	MegaSSUM (Matsuura et al., 2024) + AraMega-SSum (ours)	99,995#
Disc.	DID	ADI-17 (Shon et al., 2020) + ADI-5 (MSA only) (Ali et al., 2017)	≈2,983h
Disc.	Emo.	ANAD (Klaylat et al., 2018) + EAED (Safwat et al., 2023) + KEDAS (Belhadj et al., 2022) + KSU (Meftah et al., 2021) + YSED (Derhem et al., 2025) + ERD-MA (Ouali and El Garouani, 2025)	12.17h
Total			**5,109h + 99,995#**

Table 1: Datasets used in each training phase. Obj.denotes task objective, Gen.: generative, Disc.: discriminative, SSUM: speech summarization, TSUM: text summarization, DID: dialect identification, Emo.: emotion recognition, CV: Common Voice. "h" denotes audio duration and "#" denotes the number of samples.

Task	Benchmarks	Metric
ASR (Nat.)	LibriSpeech (Panayotov et al., 2015), MGB-2 (Ali et al., 2016)	WER
ASR (Dial.)	MGB-3 (Ali et al., 2017), SADA (Alharbi et al., 2024)	WER
ASR (L2/CS)	L2-ARCTIC (Zhao et al., 2018), ESCWA (Chowdhury et al., 2021), DACS (Chowdhury et al., 2020)	WER
Summ.	MegaSUM-SSum (Matsuura et al., 2024), AraMega-SSum (**ours**)	RL, BSc., Lj
Emotion	KSU (Meftah et al., 2021)	w-F1
DID	ADI-17 (Shon et al., 2020)	w-F1

Table 2: Evaluation datasets and metrics. Nat. denotes native, Dial.: dialectal, L2: second-language, and CS: code-switching. Summ.: summarization, RL: ROUGE-L, BSc.: BERTScore, Lj: LLM-judge and w-F1: weighted F1.

Datasets for multi-task training. For the multi-task learning experiments, we selected several datasets covering both generative and discrimina-

tive tasks, including ASR, summarization, emotion recognition, and dialect identification. Below, we briefly describe each dataset.

- **ASR:** Given the high-resource nature of ASR compared to downstream semantic tasks, we performed a controlled **subsampling of the ASR dataset**. We selected 6.44% of the dataset curated for Phase 1.
- **Summarization:** For English, we use the standard training partitions of the Mega-SSum dataset. For Arabic, we use the newly developed **AraMega-SSum** dataset. Examples from the dataset are presented in Appendix Figure 5.
- **Emotion Recognition:** We curated publicly available Arabic affective corpora, covering diverse Arabic emotional speech.
- **Dialect Identification (DID):** We unified the ADI-17 (Shon et al., 2020) corpus with the MSA partitions from the ADI-5 dataset, providing a taxonomy covering 17 Arabic dialects plus MSA.

Our final multi-task dataset aggregates approximately **5,109** hours of speech. To ensure training stability and optimize memory utilization, we constrained the duration of all speech instances to $t \leq 180$ seconds. Table 1 reports the statistics of the curated datasets. Per-task, label-wise distributions are shown in Figures 3–4 in the Appendix.

3.3 Evaluation Datasets

To assess the multi-task capabilities we curate a comprehensive evaluation suite spanning generative and discriminative tasks from publicly available test sets. Below we describe each of them as also reported in Table 2.

ASR. We benchmark transcription performance across three dimensions: native English, L2 speech, MSA and dialectal Arabic. For native English, we utilize the **LibriSpeech** (Panayotov et al., 2015) *test-clean* and *test-other* partitions. To assess the model's proficiency with non-native accents, we evaluate on the **L2-ARCTIC** test split (Zhao et al., 2018), specifically filtering for speakers with Arabic as their first language (L1) to measure L2-English phonetic adaptation. For Arabic, we employ the widely recognized **MGB-2** benchmark (Ali et al., 2016) for Modern Standard Arabic (MSA). We further evaluate the models robustness to dialectal variation and code-switching through a suite of challenging datasets:

- **Dialectal Diversity:** We use the **MGB-3** Egyptian test set (Ali et al., 2017) and the **SADA** (Alharbi et al., 2024) Saudi dialectal corpus to measure regional linguistic adaptation;
- **Code-Switching (CS):** We evaluate intra-sentential and inter-sentential dynamics using **ESCWA** (Arabic-English CS) (Chowdhury et al., 2021) and **DACS** (within-dialect CS) (Chowdhury et al., 2020).

Overall, this setup supports broad evaluation across English and Arabic, including native, non-native, dialectal, and code-switched speech.

Emotion Recognition (ER). We evaluate emotion recognition on **KSU Emotions:** acted Arabic speech (Meftah et al., 2021)

Dialect Identification (DID). We use the **ADI17** test set (Shon et al., 2020) to evaluate classification across 17 Arabic dialects. This serves as a high-granularity evaluation of the model's ability to distinguish subtle phonetic and lexical variations across the Arab world.

Summarization (SSum and TSum). We evaluate summarization using the test sets of **Mega-SSum** for English (Matsuura et al., 2024) and our proposed **AraMega-SSum** for Arabic. These benchmarks measure the models ability to generate concise, faithful summaries from short-form audio. To separate acoustic errors from summarization ability, we also include a *text-only* setting that feeds gold transcripts directly to the LLM, providing an oracle upper bound on summarization performance.

4 Experimental Setup

Baseline. For baseline comparisons, we include both open and proprietary models. As an open baseline, we evaluate Qwen2.5-Omni-3B. For proprietary baselines, we compare against GPT-audio, GPT-5-chat, and Gemini-2.5-Pro, all evaluated in zero-shot mode without any task-specific adaptation.

Two-Phase Training. We train in two phases and keep all hyperparameters fixed across all training strategies so differences are attributable to scheduling and batch construction.

- *Phase 1 Language-centric Alignment (LA).* We perform foundational alignment for 1 epoch using the ASR task. In this phase, the audio encoder and linear aligner are fully fine-tuned while for the LLM, we adapted LoRA based training.
- *Phase 2 Multi-task instruction tuning* We run the four training strategies, UM, TPC, ADS, and

TPC→ADS, for ≈10K steps. During this stage, the encoder and aligner remain frozen, and only the LoRA adapters in the LLM are updated.

For ADS, we build a global codebook with $K = 500$ clusters from a 3% subset (≈77K utterances) of the training data to capture fine-grained paralinguistic variation.

Evaluation We evaluate generative and discriminative tasks with standard metrics. For **ASR**, we report WER, applying Arabic normalization by unifying Alef/Hamza variants and removing diacritics. For **summarization**, we report ROUGE-L (Lin, 2004), BERTScore (Zhang et al., 2020), and GPT-4.1 as an LLM judge (Zheng et al., 2023). The judge scores outputs from 1--10 on clarity, conciseness, coherence, completeness, semantic alignment, accuracy, relevance, and information density (see prompts used in Figure 7). For **classification (SER and DID)**, we use weighted F1 and normalize label variants (e.g., mapping "KSA" to "Saudi Arabia") during post-processing.

5 Results and Discussion

5.1 Results Across Tasks

In Table 3, we report results, averaged over test-sets, across adaptation phases. Phase 2 multi-task training improves both models over the base and LA settings. The gains are clearest for DID, SER, and summarization.

Appendix C provides the full per-dataset breakdown. Tables 8–11 report detailed results for ASR, SSUM and TSUM, and DID. Table 10 includes LLM-as-judge results for summary tasks.

Figure 2 summarizes the same trends across task families. Panel (a) shows that adaptation sharply reduces ASR WER for Qwen2.5-Omni-7B, with UM, TPC, and TPC→ADS reaching similar WER values near 19. Panel (b) shows that UM and TPC provide the strongest summarization performance, while ADS remains below both strategies. Panel (c) reveals different behavior across the discriminative tasks: TPC→ADS achieves the strongest DID performance, whereas standalone ADS gives the best SER result. Together, these results show a task-dependent trade-off, with UM and TPC favoring generative performance and diversity-aware sampling providing task-specific gains for discriminative tasks.

Phase / Model	Generative		Discriminative	
	ASR ↓	Summ. ↑	DID ↑	SER ↑
Qwen2.5-Omni-7B				
Base	48.79	55.0	10.31	14.26
LA	21.70	54.3	9.79	16.19
UM	19.01	**66.9**	87.76	87.88
TPC	**18.97**	**66.9**	87.78	87.19
ADS	19.60	64.9	86.72	**88.30**
TPC→ADS	19.04	66.6	**88.80**	86.45
Δ TPC vs. UM	**−0.04**	0.0	**+0.02**	−0.69
Δ TPC→ADS vs. TPC	+0.07	−0.3	**+1.02**	−0.74
Gemma-4-E4B-it				
Base	22.91	54.3	21.17	14.94
LA	20.12	46.2	7.76	3.40
UM	**18.94**	67.1	78.83	75.04
TPC	19.27	**67.2**	78.55	74.76
ADS	19.75	66.0	75.93	**75.62**
TPC→ADS	19.14	66.9	**79.99**	71.01
Δ TPC vs. UM	+0.33	**+0.1**	−0.28	−0.28
Δ TPC→ADS vs. TPC	**−0.13**	−0.3	**+1.44**	−3.75
Models				
Qwen2.5-Omni-3B (Base)	54.95	46.5	7.66	8.79
GPT-audio	22.66	43.5†	38.44	21.23
Gemini-2.5-Pro	19.85	58.4	63.37	25.96

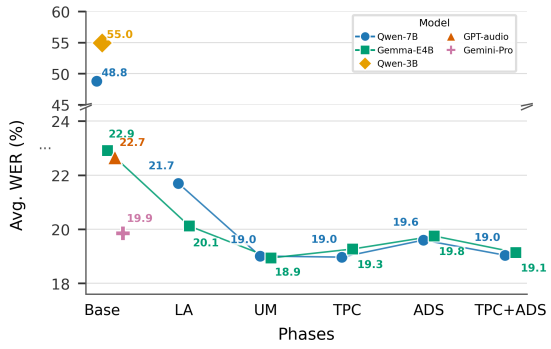
Table 3: Results across generative and discriminative tasks by phases. ASR reports WER (↓); summarization: average BERTScore F1; DID and SER report weighted-F1 (↑). SER is evaluated on KSU Emotions. †SSUM only, as GPT-audio was not run on TSUM. The shaded Δ rows decompose scheduling effects in two steps: Δ TPC vs. UM isolates the gain from curriculum ordering over the standard baseline, and Δ TPC→ADS vs. TPC isolates the additional effect of diversity-oriented sampling. **Teal**: improvement; orange: degradation.

5.2 Effect of Language-Centric Alignment

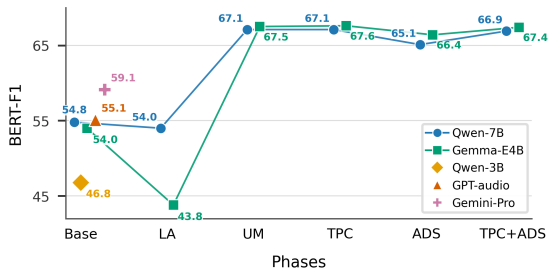
LA gives a large ASR gain. It reduces Qwen2.5-Omni-7B WER from 48.79 to 21.70. It also reduces Gemma-4-E4B-it WER from 22.91 to 20.12. This shows that Phase 1 improves language-dependent acoustic and lexical alignment. However, LA alone does not solve higher-level speech understanding. DID and SER remain weak after LA, since the LA model, trained only on plain-text transcription, mostly answers classification prompts with a transcription rather than a label, and summarization shows limited or negative gains. We therefore treat LA as a necessary alignment step, not as a complete adaptation strategy. Phase 2 multi-task instruction tuning is needed for semantic and paralinguistic behavior.

5.3 Effect of Phase 2 Data Scheduling

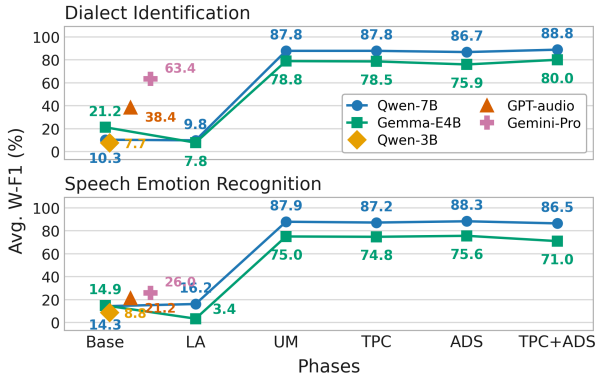
We compare UM, TPC, ADS, and TPC→ADS under the same model, optimization settings, and training budget. This design isolates the effect of



(a) ASR WER



(b) Summarization BERTScore F1



(c) DID and SER weighted-F1

Figure 2: Results across task families. Panel (a) reports average ASR WER across MSA, dialectal Arabic, code-switched speech, native English, and L2 English. Panel (b) reports average summarization BERTScore F1 over SSUM and TSUM. Panel (c) reports DID and SER weighted-F1. Lower is better for WER. Higher is better for all other metrics.

data scheduling and batch construction.

Generative tasks. UM and TPC provide the strongest results for ASR and summarization. UM benefits from stable exposure to the natural task distribution. TPC starts with ASR and gives the model a strong audio-to-text mapping before adding higher-level tasks. This helps both ASR and summarization. ADS also improves over the base setting, but it usually trails UM and TPC on generative tasks. This suggests that ASR and summarization benefit from repeated exposure to common acoustic and lexical patterns.

Discriminative tasks. The two discriminative tasks show different patterns under diversity-aware sampling. For DID, TPC→ADS consistently achieves the highest weighted-F1 for both Qwen2.5-Omni-7B and Gemma-4-E4B-it, improving over TPC by 1.02 and 1.44 points, respectively. For SER, standalone ADS performs best for both backbones, while applying ADS after TPC provides no additional benefit. These results suggest that diversity-oriented sampling can improve discriminative learning, but its effectiveness depends on the task and training schedule.

Overall trade-off. Scheduling choices have a measurable impact under limited resources. UM and TPC provide the strongest generative performance, making them preferable when ASR or summarization is the primary objective. For discriminative tasks, however, no single schedule dominates: TPC→ADS consistently achieves the best DID performance across both backbones, whereas standalone ADS performs best on SER. This indicates that diversity-aware sampling provides task-specific benefits rather than uniform gains across discriminative tasks. Notably, the adapted open models substantially outperform the zero-shot proprietary baselines on both DID and SER while remaining competitive on ASR and summarization.

6 Related Work

Audio and multimodal LLMs. Recent work has extended LLMs to speech and other modalities by aligning pretrained encoders with language decoders. Early models such as SpeechT5 learned multiple speech tasks in a shared encoder–decoder framework (Ao et al., 2022). Later systems, including AudioPaLM, SpeechGPT, and Qwen-Audio, combined LLM backbones with speech tokenization and instruction tuning for unified audio understanding and generation (Rubenstein et al., 2023; Zhang et al., 2023a; Chu et al., 2023; Sara et al., 2026). More recent omni models further scale this paradigm across modalities (Xu et al., 2025a,b; Rouditchenko et al., 2025). However, prior work gives limited attention to how data mixing affect stability and cross-task generalization in end-to-end audio instruction tuning.

Multi-task training. Multi-task audio instruc-

tion tuning is often affected by negative transfer, where dominant tasks suppress weaker or higher-level ones. Octavius addresses this problem with a LoRA-based mixture-of-experts design that reduces cross-task interference (Chen et al., 2024). MINT shows that naive task aggregation can harm generalization and that structured grouping improves transfer across tasks (Shan et al., 2025). Curriculum learning has also been shown to improve optimization when the training order is well chosen (Bengio et al., 2009). These findings motivate a systematic comparison between curriculum-style ordering and diversity-oriented sampling.

Arabic speech understanding. Arabic has benefited from multilingual speech foundation models such as Whisper and XLS-R, as well as LLM-based systems for Arabic ASR and dialect identification such as Octopus (Althubaiti et al., 2025). However, higher-level Arabic speech understanding remains underdeveloped. Arabic summarization research is still largely text-based, for example AraBART (Kamal Eddine et al., 2022). Speech emotion recognition also continues to rely on relatively small task-specific datasets such as and KSUEmotions (Meftah et al., 2021). Unified instruction-following audio models for Arabic remain largely unexplored.

7 Conclusion

We presented a controlled study of data scheduling and batch construction for multi-task instruction tuning of Arabic-centric omni audio LLMs, covering ASR, speech summarization, dialect identification, and emotion recognition. We also introduced **AraMega-SSum**, the first Arabic speech summarization benchmark. Our results show that training schedules induce distinct task-specific behaviors. UM and TPC are most effective for generative tasks, standalone ADS yields the strongest SER performance, and TPC→ADS consistently performs best on DID while maintaining competitive ASR and summarization results. This pattern suggests that curriculum ordering and diversity-aware sampling offer complementary benefits rather than a universally superior strategy: curriculum favors stable generative learning, whereas diversity-oriented sampling can strengthen discriminative learning depending on the task. These findings underscore the importance of adapting the training schedule to the objectives and data characteristics of multi-task AudioLLM systems.

Limitations

Our study evaluates two AudioLLM backbones in an Arabic–English setting, with Qwen2.5-Omni-7B as the primary model and Gemma-4-E4B-it as an architecture-sensitivity check. Although several scheduling trends are consistent across both models, their task-specific differences suggest that the findings may not generalize to other architectures, scales, or pretraining settings.

All strategies are evaluated under a fixed training and a parameter-efficient fine-tuning setup. Different results may emerge with larger budgets or full-parameter training. We also do not exhaustively ablate ADS components, which jointly combine task proportionality, label balancing, and diversity-aware sampling. Therefore, the observed SER and DID gains should be interpreted as task-dependent effects of the overall scheduling strategy rather than individual ADS components. Finally, SER is evaluated on the KSU Emotions test split, which shares speakers with the KSU training data, so SER results reflect speaker-dependent performance rather than generalization to unseen speakers.

Societal/Broader Impact

This work can improve Arabic speech technology in dialect-rich, code-switched settings, supporting accessibility (e.g., captions), education, and media/knowledge access with better transcription and spoken summarization. However, societal risks exist. Performance may vary across dialects, accents, and speaking styles, potentially creating unequal error rates and exclusion. Paralinguistic tasks (emotion/dialect recognition) can be misused if treated as definitive signals, and should not inform consequential decisions without strong validation and human oversight. Finally, AraMega-SSum relies on translation and TTS/voice cloning, which raises source-traceability and misuse concerns (e.g., impersonation) if not clearly documented. We therefore emphasize responsible release and use: transparent dataset documentation (licensing, consent, and synthetic labeling), subgroup evaluation, and explicit restrictions against surveillance or high-stakes deployment without safeguards.

Ethical Considerations

Our work leverages large-scale Arabic and English speech corpora, including synthetic audio

generated via neural voice cloning. While these methods enable the creation of diverse and balanced datasets, they raise important ethical considerations. First, the use of voice cloning and synthesized speech could potentially be misused for impersonation, fraud, or other malicious purposes. Second, even when using publicly available or synthetic data, issues of privacy and consent must be carefully managed, particularly when real speaker recordings are involved. We mitigate these concerns by curating datasets with explicit permissions where applicable, ensuring anonymization of speaker identities, and restricting dataset release to research purposes only. Future work should continue to address these risks, especially in low-resource and dialect-rich contexts where consent practices may vary.

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Appendix

A Dataset Details

Figure 3 presents the distribution of emotion labels across multiple Arabic emotion datasets used for training, including KEDAS, EAED, KSU, YSED, ERD-MA, and ANAD. Each dataset exhibits a distinct class composition, with emotions such as anger, happiness, neutrality, and sadness consistently represented, while fear, questioning, and surprise appear less frequently and vary across datasets. KEDAS and EAED contribute the largest number of samples with a broad coverage of emotion categories.

Figure 4 shows the training data covers dialects across 17 countries using the **ADI-17** dataset, along with MSA from **ADI-5**. The distribution is dominated by Egyptian, Iraqi, and Mauritanian dialects, while the remaining dialects are represented with varying but comparatively smaller sample sizes.

Figure 5 presents example samples from the MegaSSUM dataset, showing English transcriptions and summaries, alongside corresponding Arabic transcriptions and summaries from the proposed AraMega-SSum dataset. Each instance is paired with both English and Arabic speech through text-to-speech generation, enabling cross-lingual and cross-modal speech summarization training and evaluation.

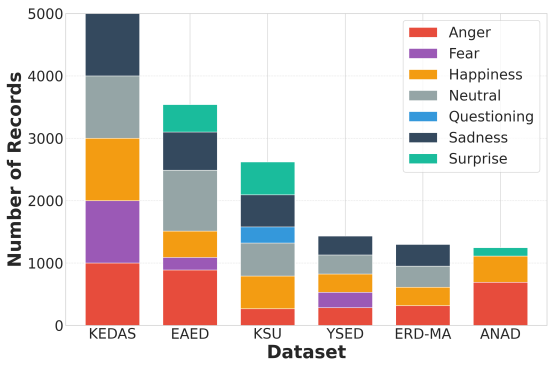

Figure 3: Emotion label distribution across training datasets.

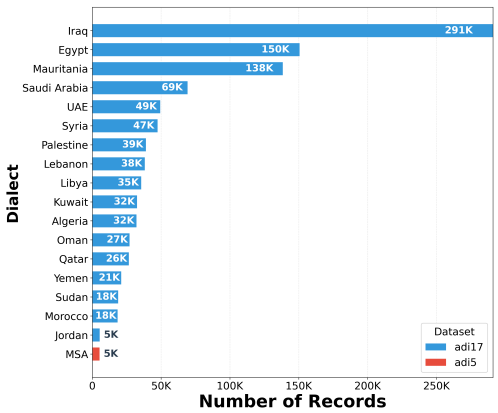

Figure 4: Dialect distribution in the training set.

English Transcription *Mega-SSum*	the yugoslav justice ministry on friday issued subpoenas to a total of ## leaders of nato and its major member countries , including u.s. president bill clinton , ordering them to appear in court on war crimes charges
English Summary *Mega-SSum*	yugoslav court issues subpoenas to nato leaders
Arabic Transcription *AraMega-SSum*	أصدرت وزارة العدل اليوغوسلافية يوم الجمعة مذكرات استدعاء إلى ما مجموعه 74 من قادة ناتو ودوله الأعضاء الرئيسية، بمن فيهم الرئيس الأمريكي بيل كلينتون، تأمرهم فيها بالمثول أمام المحكمة بتهم ارتكاب جرائم حرب
Arabic Summary *AraMega-SSum*	محكمة يوغوسلافية تصدر أوامر استدعاء بحق قادة ناتو.

English Transcription *Mega-SSum*	a man from the italy 's south city of bari committed suicide in vatican 's famous basilica of st. peter in rome thursday , shooting himself in the head while being filmed by an australian tourist
English Summary *Mega-SSum*	a man suicides in vatican 's basilica of st. peter
Arabic Transcription *AraMega-SSum*	رجل من مدينة باري جنوب إيطاليا انتحر في كنيسة القديس بطرس الشهيرة في الفاتيكان بروما يوم الخميس، مطلقاً النار على رأسه بينما كان يصوره سائح أسترالي
Arabic Summary *AraMega-SSum*	رجل ينتحر في كاتدرائية القديس بطرس بالفاتيكان

Figure 5: Sample speech summarization instances from AraMega-SSum.

B AraMega-SSum Validation

AraMega-SSum is the only newly developed semi-synthetic dataset introduced in this work. The other datasets used for ASR, emotion recognition, and dialect identification are curated from publicly available real-speech benchmarks. We therefore provide additional validation for AraMega-SSum to clarify its construction process, intended use, and quality-control procedures.

AraMega-SSum is designed to support Arabic speech summarization, a setting in which publicly available datasets with aligned speech, transcripts, and abstractive summaries remain scarce. The dataset serves as a quality-controlled semi-synthetic resource that enables controlled experimentation in this under-resourced setting.

It is derived from MegaSSum. We translate the source transcripts and abstractive summaries into Arabic using Gemini-2.5-Flash, followed by manual checks to improve semantic consistency, information preservation, contextual accuracy, completeness, and coherence. For speech generation, we use neural voice cloning conditioned on real speaker references. The generated speech is then evaluated through both human assessment and automatic quality checks.

B.1 Translation Quality

In Table 4, we present English-to-Arabic summary translations achieve near-perfect evaluation scores from a GPT-4.1 judge, consistently exceeding 9.95 out of 10 across all measured quality metrics, including semantic equivalence and coherence. On the human evaluation we observe similar scores in all rubrics as shown in Table 5.

Metric (EN→AR transfer)	Score (/10)
Semantic Equivalence	9.96
Information Preservation	9.96
Contextual Accuracy	9.96
Completeness	9.96
Coherence	9.98

Table 4: LLM-as-a-judge (GPT-4.1) scores for English→Arabic summary translation by Gemini. Scores are out of 10.

Metric (EN→AR transfer)	Score (/10)
Semantic Equivalence	9.93
Information Preservation	9.95
Contextual Accuracy	9.99
Completeness	9.95
Coherence	10.0

Table 5: Human scores for English→Arabic translation quality. Scores are out of 10.

B.2 Audio Quality

For speech generation, we use neural voice cloning conditioned on real speaker references. To validate the generated Arabic speech, we conduct both human and automatic quality checks. For the human evaluation, three paid annotators evaluate 100 randomly sampled audio clips from the test set. The annotators rate each clip on a 5-point Likert scale, where 5 means excellent, 4 good, 3 fair, 2 poor, and 1 bad. We evaluate three standard speech-quality dimensions: naturalness, audio quality, and intelligibility. As shown in Table 6, the generated speech receives good average scores across the three dimensions. We also report Gwet's AC1 (Gwet, 2008) to measure annotator agreement, which shows substantial agreement for naturalness and intelligibility and very high agreement for audio quality.

In addition to the human evaluation, we report automatic speech-quality and speaker-consistency indicators. Specifically, we compute ASR word error rate using Fanar Aura ASR, overall speech

Metric	Avg.	Gwet's AC1
Naturalness	3.975	78.9%
Audio Quality	4.373	95.0%
Intelligibility	3.692	78.9%

Table 6: Human speech-quality evaluation of 100 randomly sampled AraMega-SSum test-set audio clips.

quality using NISQA, and speaker cosine similarity between the generated audio and the corresponding speaker reference. The generated speech obtains a Fanar Aura ASR WER of 15.5, a NISQA score of 3.95 out of 5, and cosine similarity of 0.664. These values are acceptable and consistent with prior studies (Alam et al., 2025).

Overall, these results show that AraMega-SSum is a quality-controlled semi-synthetic resource for Arabic speech summarization. The dataset fills an important resource gap while keeping its semi-synthetic nature explicit. We therefore use it as a controlled benchmark for Arabic speech summarization experiments.

B.3 Real vs. Synthetic Speech

To assess whether our summarization results depend on synthetic speech, we collect real recordings for 250 items from the AraMega-SSum test set. Two native speakers read the sentences in Modern Standard Arabic using the same in-house annotation platform used for quality checks. We evaluate five models under both conditions: Qwen2.5-Omni-7B and Gemma-4-E4B-it in base and TPC $\rightarrow$ ADS settings, and Gemini-2.5-Pro as a proprietary baseline.

As shown in Table 7, the two conditions yield nearly identical BERTScore F1. No model differs by more than 0.50 points, and four of the five score higher on real speech. A paired bootstrap over per-item scores (10k resamples) finds four of the five differences indistinguishable from zero ($p > 0.10$); only Gemma-4-E4B-it (base) differs significantly, by 0.50 points in favor of real speech ($p = 0.013$). The margin between base models and their TPC $\rightarrow$ ADS counterparts is preserved, at 8.7 to 8.8 BERTScore points on synthetic speech and 7.9 to 8.5 on real speech. Overall, these results show that synthetic speech in AraMega-SSum does not inflate summarization performance and that findings transfer to real speech.

C Additional Results

In Table 8, we provide a detailed ASR breakdown across language varieties and speech conditions.

Model	Synthetic	Real	Δ
Qwen2.5-Omni-7B (base)	54.85	55.31	+0.46
+ TPC $\rightarrow$ ADS	63.60	63.85	+0.26
Gemma-4-E4B-it (base)	54.49	54.98	+0.50
+ TPC $\rightarrow$ ADS	63.16	62.84	-0.32
Gemini-2.5-Pro	56.80	57.15	+0.35

Table 7: BERTScore F1 on synthetic vs. real speech for the same 250 AraMega-SSum test items.

The results show that adaptation consistently improves over the base Qwen2.5-Omni-7B model across MSA, dialectal Arabic, code-switched speech, native English, and L2 English. LA gives large gains over the base model, especially for English ASR, but the multi-task phases further improve Arabic and code-switched speech. For Qwen2.5-Omni-7B, TPC and TPC→ADS achieve the strongest Arabic and code-switching results, while UM remains highly competitive. For Gemma-4-E4B-it, UM and TPC→ADS perform best across most Arabic and code-switched settings, with TPC→ADS giving the lowest WER on several dialectal and code-switched benchmarks. The closed models perform strongly on some subsets, but the adapted open models remain competitive, especially on MSA, English, and several dialectal or code-switched conditions. Overall, the breakdown supports the aggregate ASR trends and shows that adaptation improves robustness across diverse speech conditions.

Table 9 reports SSUM and TSUM results in English and Arabic using ROUGE-1, ROUGE-L, and BERTScore. Multi-task adaptation improves Qwen2.5-Omni-7B and Gemma-4-E4B-it over base and LA settings on most metrics. For Qwen, UM and TPC perform best on SSUM, while TPC and TPC→ADS lead on TSUM. For Gemma, UM is strongest on SSUM, whereas TPC and TPC→ADS lead on TSUM. Overall, UM and TPC provide strong summarization performance, with TPC→ADS yielding gains in TSUM settings.

Table 10 reports LLM-as-a-judge scores for SSUM across English and Arabic. The judge scores are broadly consistent with the automatic metrics: UM and TPC remain competitive across both models, ADS scores lowest among adapted phases, and Gemini-2.5-Pro leads overall.

Table 11 reports ADI17 dialect identification results. Multi-task adaptation substantially improves both models over base and LA settings. For Qwen2.5-Omni-7B, TPC→ADS achieves the best accuracy, macro-F1, and weighted-F1; for

Model	Phase	MSA	DA		CS		En L1		En L2
		MGB2	MGB3	SADA	ESCWA	DACS	Libri-clean	Libri-other	L2-Arctic
Qwen2.5-Omni-7B	Base	33.48	54.59	76.62	61.91	45.53	41.51	39.20	37.47
Qwen2.5-Omni-7B	LA	13.51	31.53	54.87	42.53	22.72	1.46	2.96	4.02
Qwen2.5-Omni-7B	UM	12.98	27.49	43.61	40.70	20.09	1.48	2.82	2.90
Qwen2.5-Omni-7B	TPC	12.98	27.46	43.66	40.31	19.94	1.45	2.86	3.10
Qwen2.5-Omni-7B	ADS	13.50	27.98	44.02	43.32	20.18	1.47	2.93	3.39
Qwen2.5-Omni-7B	TPC→ADS	13.21	27.28	43.79	40.64	20.06	1.48	2.90	2.95
Gemma-4-E4B-it	Base	16.70	30.97	42.60	43.81	22.70	3.86	9.34	13.30
Gemma-4-E4B-it	LA	13.77	26.87	44.32	34.37	19.79	2.57	6.59	12.64
Gemma-4-E4B-it	UM	12.42	24.05	40.06	41.95	17.57	2.27	5.85	7.31
Gemma-4-E4B-it	TPC	12.88	23.95	40.27	43.15	17.98	2.27	5.90	7.74
Gemma-4-E4B-it	ADS	13.36	24.48	43.39	40.90	18.52	2.58	6.22	8.53
Gemma-4-E4B-it	TPC→ADS	13.00	23.81	39.65	39.99	17.97	2.28	5.99	10.45
Qwen2.5-Omni-3B	Base	45.79	62.43	85.41	71.50	57.16	33.74	35.45	48.13
GPT-audio	Base	14.44	30.38	46.88	33.52	22.97	7.16	10.70	15.25
Gemini-2.5-Pro	Base	18.98	26.55	34.91	38.92	20.18	3.70	6.84	8.70

Table 8: Detailed ASR WER results across language varieties and speech conditions. We report WER for MSA, dialectal Arabic, Arabic–English code-switching, dialect–MSA code-switching, native English, and L2 English. Lower scores indicate better performance.

Model	Phase	SSUM						TSUM					
		English			Arabic			English			Arabic		
		R-1↑	R-L↑	B-F1↑	R-1↑	R-L↑	B-F1↑	R-1↑	R-L↑	B-F1↑	R-1↑	R-L↑	B-F1↑
Qwen2.5-Omni-7B	Base	29.37	26.48	57.37	23.70	21.53	53.75	25.67	23.30	51.13	29.84	27.56	57.86
Qwen2.5-Omni-7B	LA	25.75	23.05	56.61	23.84	21.69	53.59	24.35	21.87	52.87	25.34	23.11	54.22
Qwen2.5-Omni-7B	UM	46.23	**43.62**	**69.79**	36.74	34.71	63.14	48.14	45.41	70.78	38.20	36.06	**63.97**
Qwen2.5-Omni-7B	TPC	**46.36**	43.61	69.75	**36.75**	**34.74**	**63.21**	**48.26**	**45.55**	**70.85**	38.16	36.09	63.89
Qwen2.5-Omni-7B	ADS	41.43	38.79	67.32	33.66	31.65	61.23	43.56	40.86	68.41	35.77	33.66	62.52
Qwen2.5-Omni-7B	TPC→ADS	45.16	42.40	69.20	36.14	34.14	62.92	47.78	45.13	70.60	**38.28**	**36.16**	63.85
Gemma-4-E4B-it	Base	25.98	23.20	56.02	24.39	22.21	54.04	23.19	20.78	49.47	29.75	27.35	57.51
Gemma-4-E4B-it	LA	20.53	18.32	50.31	24.00	21.85	53.70	1.86	1.71	25.60	26.24	23.96	55.02
Gemma-4-E4B-it	UM	**45.32**	**42.57**	**69.05**	**37.49**	**35.46**	**63.53**	49.46	46.71	71.19	39.89	37.76	64.80
Gemma-4-E4B-it	TPC	45.03	42.31	68.87	36.76	34.81	63.37	**50.09**	**47.20**	**71.46**	39.76	37.69	64.90
Gemma-4-E4B-it	ADS	42.48	40.01	67.71	34.46	32.55	61.97	48.22	45.30	70.52	38.01	35.78	63.70
Gemma-4-E4B-it	TPC→ADS	43.98	41.24	68.34	36.34	34.27	63.07	49.78	46.81	71.30	**40.04**	**37.99**	**64.99**
Qwen2.5-Omni-3B	Base	13.13	11.79	38.90	22.05	19.95	52.49	14.36	12.95	38.33	27.68	25.31	56.34
GPT-audio	Base	5.48	5.21	29.62	28.63	26.24	57.42	–	–	–	–	–	–
GPT-5-chat	Base	–	–	–	–	–	–	34.08	30.87	60.83	31.07	28.56	59.41
Gemini-2.5-Pro	Base	28.48	25.75	57.01	27.70	25.40	56.15	33.20	30.35	59.74	34.13	31.59	60.55

Table 9: Detailed summarization results for SSUM and TSUM across English and Arabic. We report ROUGE-1, ROUGE-L, and BERTScore F1 (B-F1). Higher scores indicate better performance. Bold marks the best score within each adapted open-model block.

Model	Phase	EN↑	AR↑
Qwen2.5-Omni-7B	Base	8.82	7.26
Qwen2.5-Omni-7B	LA	6.87	7.55
Qwen2.5-Omni-7B	UM	8.66	7.66
Qwen2.5-Omni-7B	TPC	8.63	7.65
Qwen2.5-Omni-7B	ADS	8.13	7.23
Qwen2.5-Omni-7B	TPC→ADS	8.58	7.61
Gemma-4-E4B-it	Base	8.13	7.95
Gemma-4-E4B-it	LA	6.45	7.79
Gemma-4-E4B-it	UM	**8.37**	7.71
Gemma-4-E4B-it	TPC	8.31	**7.74**
Gemma-4-E4B-it	ADS	8.11	7.34
Gemma-4-E4B-it	TPC→ADS	8.29	7.65
Qwen2.5-Omni-3B	Base	6.32	6.59
GPT-audio	Base	6.60	8.97
Gemini-2.5-Pro	Base	**9.03**	**9.01**

Table 10: LLM-as-a-judge scores for SSUM across English and Arabic (out of 10). Higher is better. Bold marks the best score within each adapted open-model block and among baselines respectively.

Gemma-4-E4B-it, it gives the best accuracy and weighted-F1, while UM yields the best macro-F1. Overall, TPC→ADS provides the strongest DID performance across both backbones.

D Training Loss

Figure 6 shows the smoothed training loss for the four multi-task schedules, all initialized from the same ASR-aligned LoRA checkpoint and differing only in data ordering and sampling. UM randomly mixes all tasks, while TPC orders them from easier to harder within each epoch; the curriculum restart produces the intra-epoch U-shape visible for Gemma. ADS uses diversity-aware round-robin sampling over aligner-embedding clusters, giving a higher initial loss but the lowest final loss on both backbones. TPC→ADS uses two curriculum epochs followed by one ADS epoch; the switch near step 6356 causes a brief

Model	Phase	Acc. ↑	M-F1 ↑	W-F1 ↑
Qwen2.5-Omni-7B	Base	13.77	7.56	10.31
Qwen2.5-Omni-7B	LA	5.93	0.02	9.79
Qwen2.5-Omni-7B	UM	87.91	82.80	87.76
Qwen2.5-Omni-7B	TPC	87.93	87.71	87.78
Qwen2.5-Omni-7B	ADS	86.77	77.49	86.72
Qwen2.5-Omni-7B	TPC→ADS	**88.85**	**88.80**	**88.80**
Gemma-4-E4B-it	Base	26.62	17.76	21.17
Gemma-4-E4B-it	LA	4.27	0.01	7.76
Gemma-4-E4B-it	UM	79.28	**78.89**	78.83
Gemma-4-E4B-it	TPC	79.03	78.57	78.55
Gemma-4-E4B-it	ADS	76.03	71.79	75.93
Gemma-4-E4B-it	TPC→ADS	**80.12**	75.68	**79.99**
Qwen2.5-Omni-3B	Base	11.14	7.14	7.66
GPT-audio	Base	40.96	25.04	38.44
Gemini-2.5-Pro	Base	65.09	59.85	63.37

Table 11: Detailed dialect identification results on ADI17. We report accuracy, macro-F1, and weighted-F1. Higher scores indicate better performance. Bold marks the best score within each adapted open-model block, and underlining marks the second best.

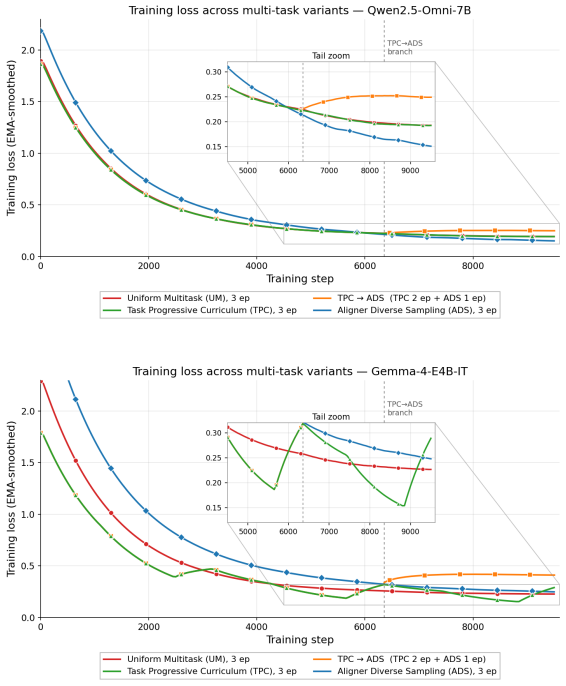

Figure 6: Training loss across multi-task schedules for Qwen2.5-Omni-7B (top) and Gemma-4-E4B-IT (bottom).

loss increase before training re-stabilizes. UM and TPC reach similar final losses (about 0.19 for Qwen and 0.23 for Gemma), indicating comparable convergence under matched compute.

E Prompts

In Figures 7, 8, and 9, we present the prompts used for LLM-as-judge summarization evaluation, LLM-as-judge translation evaluation, and model training.

```
SYSTEM_PROMPT = """You are a reference-grounded summarization
      quality evaluator.
Grade a predicted summary by comparing it with the reference
      summary.
Do NOT use outside knowledge. Judge in the same language as
      the summaries
(Arabic or English). Return ONLY a valid JSON object that
      matches the
schema exactlyno extra text.

Score each criterion as an INTEGER from 1 to 10 (1=poor,
      10=excellent):

- Clarity
- Conciseness
- Coherence
- Completeness
- Semantic_Alignment
- Accuracy
- Relevance
- Information_Density

"""

USER_PROMPT_TEMPLATE = """Language: {language}
Reference summary: {reference_summary}
Predicted summary: {predicted_summary}

Evaluate the predicted summary by comparing it with the
      reference summary.
Output only the JSON described in the system prompt."""
```

Figure 7: **Prompt used for LLM-as-a-judge summarization evaluation.**

```
SYSTEM_PROMPT = """You are an expert translation evaluator.

You will be given:
- An English transcription (may contain anonymized
  tokens such as ###, ####, and other placeholders)
- An Arabic transcription translated from the same
  English content

Your task is to evaluate how semantically equivalent
the two transcriptions are.

Evaluation Rules (STRICT):
1. Ignore all anonymization tokens in English.
2. Ignore number differences caused by anonymization.
3. Ignore name differences and transliteration variants.
4. Be lenient with phonetic spellings in Arabic.
5. Focus only on semantic meaning and core information.
6. Judge events, facts, actions, relationships, and intent.

Score each criterion as an INTEGER from 1 to 10:
- semantic_equivalence
- information_preservation
- contextual_accuracy
- completeness
- coherence

Return ONLY a valid JSON object matching the schema.
"""

USER_PROMPT_TEMPLATE = """Arabic translation:
{arabic_transcription}

Original English source:
{english_transcription}

Evaluate the Arabic translation relative to the English
source. Follow the system-prompt evaluation rules.
Return only the required JSON output."""
```

Figure 8: **Prompt used for LLM-as-a-judge translation evaluation.**

```
Phase 1: Language-centric Alignment (LA)

System
You are a multilingual speech-transcription assistant. Transcribe the provided audio accurately and in its original language.
      Follow the user instructions for output formatting exactly. Return only the transcription with no extra text.

ASR
<audio>
Transcribe the following speech segment in its original language. Follow these specific instructions for formatting the answer:
* Only output the transcription, with no newlines.
* When transcribing numbers, write the digits, i.e. write 1.7 and not one point seven, and write 3 instead of three.

Phase 2: Multi-task Instruction Tuning (UM, TPC, ADS, TPC->ADS)

System
You are an Arabic-focused speech and language assistant. Each turn provides an input  audio, text, or both  together with an
      instruction that specifies the task and the exact output format. Follow the instruction precisely: ground every response
      in the given input, preserve its original language exactly (including numbers, names, and code-switching), and return
      only what the instruction asks for, in the exact format requested.

ASR
<audio>
Task: Transcription.
Transcribe the audio accurately in its original language.
Respond with a single-line JSON object only:
{"transcription":"<text>"}

Dialect
<audio>
Task: Dialect Identification.
Identify the dialect spoken in the audio.
Choose exactly one label from the following list:
Algeria, Egypt, Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania,
Modern Standard Arabic, Morocco, Oman, Palestine, Qatar, Saudi Arabia,
Sudan, Syria, United Arab Emirates, Yemen

Respond with a single-line JSON object only:
{"dialect":"<dialect>"}

Emotion
<audio>
Task: Emotion Identification.
Identify the primary emotion expressed in the audio.
Choose exactly one emotion from the following list:
Anger, Fear, Happiness, Neutral, Questioning, Sadness, Surprise

Respond with a single-line JSON object only:
{"emotion":"<emotion>"}

SSUM
<audio>
Task: Speech Summarization.
Summarize the main content of the audio concisely.
Preserve the original language of the speech.

Respond with a single-line JSON object only:
{"summary":"<text>"}

TSUM
Task: Text Summarization.
Read the following text:
"{text}"

Summarize it concisely in the same language.
Respond with a single-line JSON object only:
{"summary":"<text>"}
```

Figure 9: **System and user prompts used for training.** Phase 1 (LA) uses a transcription-specific system prompt with plain-text output. Phase 2 uses a single unified system prompt for all tasks and all four scheduling strategies, and the same system prompt is used at inference. Each Phase 2 task prompt also has an Arabic-language variant (not shown), which is used for approximately half of the training instances of that task.