SEA-SPEECHBENCH: A Large-Scale Multitask Benchmark for Speech Understanding Across Southeast Asia

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Abstract

The rapid advancement of audio and multimodal large language models has unlocked transformative speech understanding capabilities, yet evaluation frameworks remain predominantly English-centric, leaving Southeast Asian (SEA) languages critically underrepresented. We introduce SEA-SPEECHBENCH, the first large-scale multitask benchmark that evaluates speech understanding in 11 SEA languages through 97,194 samples across 99 evaluation sets and 597 hours of curated audio data. Our benchmark comprises 9 diverse tasks across 3 categories: speech processing (automatic speech recognition, speech translation, spoken question answering), paralinguistic analysis (emotion, gender, age, speaker recognition), and temporal understanding, a novel dimension featuring timestamped content queries and temporal localization within extended audio sequences up to 3 minutes. We implement multilingual prompting in both native SEA languages and English to reflect user interactions with audio-language models. Evaluation of leading open-source and proprietary systems reveals marked performance gaps. Across all models, performance remains underwhelming on temporal understanding, emotion recognition, and speech translation. Prompting in low-resource languages such as Burmese, Lao, Tamil, and Khmer lag behind English by up to 20%. Our findings expose critical model limitations and underscore the need for inclusive model development. We will release datasets and the evaluation framework upon paper publication to facilitate reproducible benchmarking.

1 Introduction

Recent advancement in audio large language models (AudioLLMs) has led to transformative applications in voice assistants, transcription, accessibility technologies, and multimodal reasoning (Wu et al., 2024; Gemini Team, 2025; Zhang et al., 2023). Despite these advances, research in speech understanding has been disproportionately concentrated on high-resource languages, particularly English and a small number of European and East Asian languages (Yang et al., 2021; Wang et al., 2021; Bu et al., 2017). While recent benchmarking efforts (Sakshi et al., 2024; Wang et al., 2024; Yang et al., 2024) have made significant strides in evaluating audio-language models across diverse tasks and modalities, they universally overlook Southeast Asian (SEA) languages, leaving an entire linguistic region underexplored despite representing over *650 million speakers* worldwide.

Developing comprehensive benchmarks for SEA languages also presents unique technical challenges. The region's speech landscape is characterized by extraordinary linguistic diversity, rich tonal and phonetic structures, and substantial resource disparities across languages: factors that create evaluation complexities absent from English-centric benchmarks. Many SEA languages operate in low-resource contexts with limited annotated data and sparse digital representation, making robust evaluation both methodologically challenging and critically important for equitable technological development. While recent initiatives, such as MERaLiON (MERaLiON Team, 2024) which targets Singapore's multilingual context, Typhoon2-Audio (Pipatanakul et al., 2024) which focuses on Thai, and SeaLLMs-Audio (Liu et al., 2025) which extends capabilities to selected SEA languages, have begun to build general-purpose speech-language models for the SEA region, these efforts remain limited in both scope and linguistic coverage. Crucially, they lack comprehensive evaluation frameworks necessary to systematically assess capabilities across the full spectrum of Southeast Asian speech understanding tasks. Meanwhile, fragmented data collection efforts across research groups have yielded heterogeneous SEA datasets (Lovenia and et al., 2024; Pham et al., 2023; Bustamin et al., 2024; Magic Data Technol-

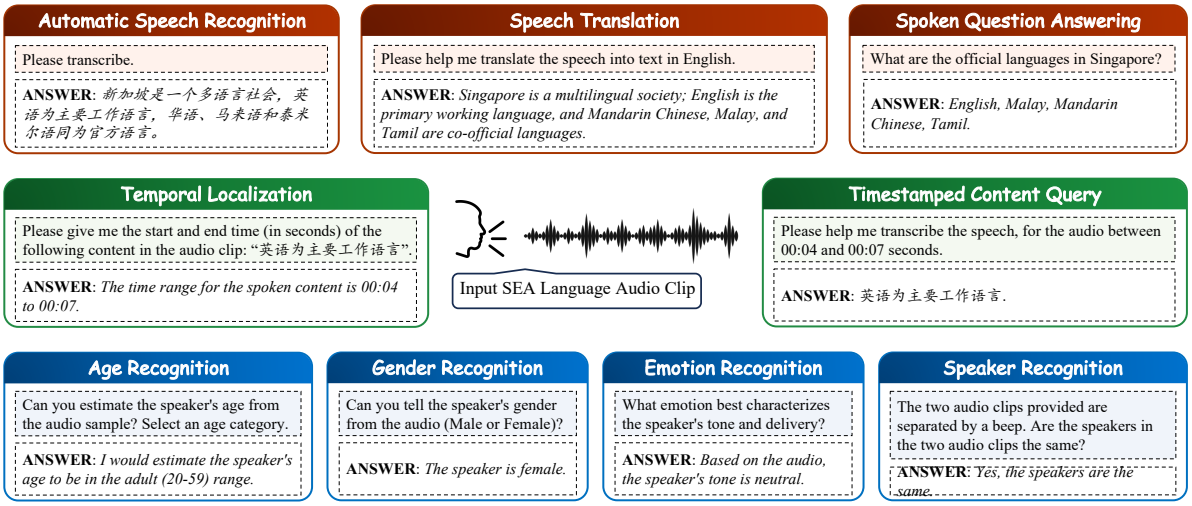


Figure 1: Overview of SEA-SPEECHBENCH task suite. The suite covers nine tasks in three categories. ■ **Speech processing**, ■ **Paralinguistic**, and ■ **Temporal reasoning**.

Table 1: Southeast Asian countries and their official language(s). Note: Several countries recognize additional regional or minority languages at sub-national levels; this table lists state-level official languages corresponding to the language codes used in our benchmark.

Country	Official language(s)	ISO 639-1 Code(s)
Singapore	English, Malay, Mandarin Chinese, Tamil	en, ms, zh, ta
Malaysia	Malay (Bahasa Melayu)	ms
Indonesia	Indonesian (Bahasa Indonesia)	id
Philippines	Filipino / Tagalog, English	tl, en
Thailand	Thai	th
Cambodia	Khmer (Cambodian)	km
Lao PDR	Lao	lo
Myanmar	Burmese (Myanmar)	my
Vietnam	Vietnamese	vi

ogy, 2025), but without unified frameworks for task definitions, prompting, and normalization, standardized comparison remains difficult.

In this work, we introduce the first ever comprehensive benchmark for speech understanding in Southeast Asian languages, designed to evaluate the capabilities of general-purpose speech-text LLMs. We focus on the official languages of Southeast Asian countries, as in Table 1, to balance broad regional coverage and practical relevance.

Our benchmark encompasses 11 SEA languages with over 597 hours of audio data, curated from existing sources and synthesized into new tasks and datasets through systematic processing. The benchmark spans 9 diverse tasks across 3 broad categories: speech processing, paralinguistics, and temporal reasoning. We introduce two tasks that evaluate models' capacity for temporal reasoning and localization within audio streams, addressing a previously unexplored dimension in audio LLM evaluation. These tasks test models' ability to navigate time-dependent information and extract content from specific temporal locations. The complete task suite is illustrated in Figure 1. To better reflect authentic usage scenarios, we evaluate each task using both English and native language text prompts.

The main contributions of this paper are threefold. First, we present SEA-SPEECHBENCH, the first ever large-scale multitask benchmark that systematically evaluates speech processing, paralinguistic analysis, and temporal reasoning across Southeast Asian languages. It comprises a total of 99 evaluation sets with more than 97,000 audio samples. Second, we introduce temporal reasoning tasks that assess models' ability to reason about time-dependent information in extended audio sequences. Finally, we comprehensively evaluate both open-source and proprietary models, offering critical insights into their strengths, limitations, and areas for further research.

2 SEA-SPEECHBENCH Evaluation Suite

2.1 Task Suite

SEA-SPEECHBENCH comprises 9 core tasks across 3 categories: *speech processing*, *paralinguistic analysis*, and *temporal reasoning*. All tasks require models to produce textual responses given an audio input and a text query.

Speech processing covers three fundamental capabilities: Automatic Speech Recognition (ASR), Speech Translation (ST) from Southeast Asian languages to English, and Spoken Question Answering (SQA) based on SEA speech inputs.

Paralinguistic analysis examines vocal cues beyond linguistic content. It includes four tasks: Emotion Recognition (ER), which classifies emotional

Table 2: Summary of curated datasets for SEA-SPEECHBENCH. For multilingual datasets, each language-specific sub-dataset is counted separately in #Datasets.

Task	Languages	#Datasets	#Samples	Total L (h)	Min L (s)	Max L (s)
ASR	en tl id km lo ms my ta vi zh th	33	26,863	52.88	0.47	30.00
ST	en tl id km lo ms my vi th	9	7,189	26.46	3.06	30.00
SQA	en zh id th vi	7	5,462	40.57	20.00	30.00
ER	zh id th en ta	7	5,356	5.33	0.12	29.86
GR	zh id th en ta vi km my	16	13,599	22.02	0.12	29.90
AgeR	zh th en ta vi	5	4,608	6.55	0.58	20.78
SpkR	zh th en ta vi my	8	7,827	19.72	2.10	30.38
TCQ	zh en th id vi	7	13,145	211.98	20.00	180.00
TLoc	zh en th id vi	7	13,145	211.98	20.00	180.00
Total	–	**99**	**97,194**	**597.49**	–	–

states; Gender Recognition (GR), which predicts gender from voice characteristics; Age Recognition (AgeR), which categorizes speakers as teens (10–19), adults (20–59), or seniors (60–100); and Speaker Recognition (SpkR), which determines whether two clips belong to the same speaker.

Temporal reasoning introduces two novel tasks designed for extended audio, motivated by "skip to the content" and "what's said at this time" use cases. Timestamped Content Query (TCQ) requires extracting content within a specified interval $[t_s, t_e]$, testing temporal grounding and localized retrieval. Temporal Localization (TLoc) asks models to predict the exact time span $\hat{y} = [\hat{t}_s, \hat{t}_e]$ where queried information appears, evaluating boundary detection and alignment. Both tasks are constructed from the same set of extended audio recordings, differing only in the direction of the query (content-to-time versus time-to-content). Together, these tasks formalize time-referenced retrieval and support fine-grained navigation across recordings.

The first two categories use short clips ($\leq$ 30s) to align with most current model input limits. As real-world audio applications increasingly involve longer recordings where users require temporal navigation, SEA-SPEECHBENCH introduces the temporal reasoning tasks to assess model ability to perform reasoning and localization over extended sequences of up to 3 minutes.

2.2 Data Curation and Processing

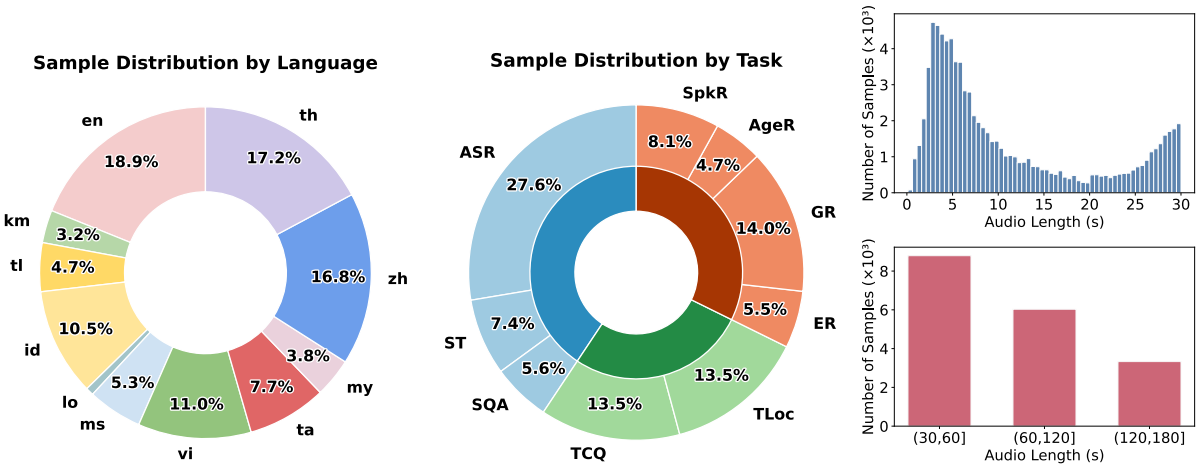
Dataset Statistics: As shown in Table 2, SEA-SPEECHBENCH is a comprehensive benchmark comprising of over 97,000 samples across 9 tasks and 11 Southeast Asian languages.

Traditional speech processing tasks span the broadest linguistic coverage with standard 30-second clips, while our novel temporal understanding tasks focus on 5 key languages with extended recordings up to 180 seconds. Detailed information for each source dataset is provided in Appendix A.

Language and Task Distribution: Figure 2 reveals the linguistic and task composition of our benchmark. The language distribution (Figure 2a) demonstrates substantial coverage across Southeast Asian languages, with English (18.9%), Thai (17.2%) and Chinese (16.8%) representing the largest segments, followed by Vietnamese (11.0%) and Indonesian (10.5%). We also include low-resource languages such as Khmer and Lao to ensure representation of the region's full linguistic spectrum. Figure 2b shows balanced coverage across evaluation task families.

Audio Length Distribution: We cover both short and long audios to enable more comprehensive and realistic evaluation. As shown in Figure 2c, our benchmark encompasses a broad distribution of utterances spanning 0–30 seconds, with natural concentration around sentence-length segments for traditional tasks. For temporal understanding evaluation, we systematically curate extended recordings through strategic segmentation of long-form datasets, creating stratified duration bins of 30–60s, 60–120s, and 120–180s, totaling over 10,000 samples for long audios.

Data Processing: We applied uniform data processing across all datasets and synthesized additional evaluation sets for tasks lacking suitable ex-



(a) Sample distribution by language. Colors match Table 2 language tags.

(b) Sample distribution by task.

(c) Audio duration distribution overview.

Figure 2: SEA-SPEECHBENCH composition: (a) language distribution by audio hours, (b) task distribution by sample count, and (c) audio duration distribution. (Upper: short audios ($\leq$ 30s) with fine-grained histogram. Lower: long audios ($>$ 30s) aggregated into three duration ranges.)

isting data.

We unify all data sources into a consistent triplet format audio context, text instruction, text answer with paired audio/text fields. All audios are converted to a standard representation by downmixing to mono when needed, resampling to 16 kHz, applying peak normalization to control amplitude variations, and storing the waveform in an OGG/OPUS container to ensure consistent decoding and comparable inference conditions across datasets. For evaluation, we sample a fixed-size test set per language and duration bin (up to 1,000 instances) with a fixed random seed for reproducibility. Also, we enforce a speaker-disjoint split: segments associated with the same speaker are assigned to a single split only, so no speaker appears in both train and test. Within each split, candidates are filtered by our quality criteria and then sampled to match the target size, with a minimum-count safeguard for low-resource bins.

For long-form recordings requiring timestamped queries (e.g., TCQ/TLoc), segments are built from contiguous speech within the same recording and may span multiple utterances as long as the inter-utterance gap is at most 5 seconds. Segments are terminated when the duration exceeds a target bin (e.g., 60–120s), the gap between utterances exceeds 5 seconds, or utterance-level alignment confidence is low (CTC log-probability < -2). To ensure sufficient semantic content, we apply a speech-density filter (words-per-second for space-delimited languages; characters-per-second otherwise) and remove templated or boilerplate phrases. We further filter using CTC-confidence thresholds at both utterance and segment levels, and perform language identification using the Lingua Python language-detection library on the concatenated transcript, retaining segments only when the predicted ISO-639-1 code matches the target language. Finally, we deduplicate segments by transcript to remove near-duplicates. More data processing and synthesis details are provided in Appendix B.

2.3 Metrics

Table 3 presents each task's output format and primary evaluation metric. For ASR and TCQ, where the expected outputs are text transcripts, we employ script-dependent error rates: Character Error Rate (CER) for languages without explicit word boundaries (Chinese (zh), Thai (th), Khmer (km), Lao (lo), and Burmese (my)), and Word Error Rate (WER) for the other space-delimited languages. For ST, we use the BLEU score to measure n-gram overlap between generated translations and reference texts. For TLoc, given a actual time span $y = [t_s, t_e]$ and a prediction $\hat{y} = [\hat{t}_s, \hat{t}_e]$, define the intersection $I = \left[\min(\hat{t}_e, t_e) - \max(\hat{t}_s, t_s)\right]_+$ with $[x]_+ = \max(x, 0)$. Coverage and purity are $C = \frac{I}{t_e - t_s}$ and $P = \frac{I}{\hat{t}_e - \hat{t}_s}$, and the metric is $F1 = \frac{2CP}{C+P}$ for $C + P > 0$ (otherwise $F_1 = 0$).

Model-As-Judge: For the other tasks, due to the inherent variability of free-form outputs, we employ an LLM-based judge for consistent evaluation, adapted based on the methodology proposed in (Wang et al., 2024). For SQA, the judge assigns a 0–5 quality score; we report this as a percentage via

Table 3: Outputs and metrics by task. † *Judge-provided metrics*: scores are produced by a LLM serving as an external judge.

Task	Expected Output	Metric(s)
ASR	Text transcript	**WER/CER**
ST	Text translation	**BLEU**
SQA	Short textual answer	**Scaled judge score** s_{SQA} †
AgeR	Age bin ∈ {teens, adults, seniors}	**Judge-based classification Acc** †
ER	Emotion label	
GR	Gender label ∈ {male, female}	
SpkR	Speaker identity match or mismatch	
TCQ	Text transcript at given time	**WER/CER**
TLoc	Time span $[t_s, t_e]$	$F1$ **score**

Table 4: Consistency between LLM-judged scores and human evaluator scores for English and SEA prompts. Alignment is quantified using Matthews correlation coefficient (MCC) for binary classification tasks and Spearman rank correlation (ρ) for ordinal ratings.

	MCC (Eng)	ρ (Eng)	MCC (SEA)	ρ (SEA)
Qwen3-Omni-30B-A3B-Instruct	0.81	0.80	0.76	0.37
Gemma-3-27B-Instruct	**0.98**	0.82	**0.97**	0.66
GPT-4.1	**0.98**	**0.84**	**0.97**	**0.76**

a linear scaling $s_{SQA} = 20 \times \text{score}, \ \text{score} \in \mathbb{Z}_{[0,5]}$. For paralinguistic tasks (ER, GR, AgeR, SpkR), the judge canonicalizes outputs and renders binary correctness, reported as accuracy in percent. Detailed judging prompts are provided in the Appendix F.

2.3.1 Assessment of Model Judge

To assess alignment with human judgment, we conduct an expert human evaluation for three model judges: Gemma3-27B-Instruct (Team, 2025), Qwen3-Omni-30B-A3B-Instruct (Xu et al., 2025b), and GPT-4.1 (OpenAI, 2024a), using a uniform evaluation protocol on a representative subset of tasks. We analyze judge–human agreement separately for English prompts and SEA language prompts. For each task and language, we randomly selected 100 model responses and collected the model judge scores and the human evaluator scores by native-speaker annotators. Alignment is quantified using Matthews correlation coefficient (MCC) for binary classification tasks and Spearman rank correlation (ρ) for ordinal ratings for SQA. Quantitative results are summarized in Table 4.

For all English prompts and binary classification settings, Gemma-3-27B Instruct and GPT-4.1 both exhibit strong and comparable alignment with human annotations. However, for SEA language prompts with ordinal rating scales, GPT-4.1 achieves substantially higher judge–human correlation than Gemma-3 ($\rho = 0.76$ vs. $\rho = 0.66$, averaged across SEA languages). Balancing both evaluation performance and computational cost, we therefore adopt a hybrid judging strategy: GPT-4.1 serves as the judge for SQA task, while Gemma-3-27B-Instruct is deployed in binary judge tasks.

3 Evaluations

3.1 Evaluation Setting

We conduct extensive evaluation across several state-of-the-art open-source audio/multimodal LLMs with multiple size variants ranging from 2B to 30B parameters: MERaLiON-2 (MERaLiON Team, 2024), SeaLLMs-audio (Liu et al., 2025), Phi-4-multimodal-instruct (Microsoft, 2025), Qwen2-Audio-Instruct (Chu et al., 2024), Qwen2.5-Omni (Xu et al., 2025a), Gemma-3n-it (Gemma Team, 2025), Voxtral (Voxtral Team, 2025), Kimi-audio (KimiTeam, 2025), and Qwen3-Omni and its thinking model (Xu et al., 2025b). All models are evaluated using their official released checkpoints with recommended inference configurations to ensure fair comparison. To establish comprehensive performance baselines, we also evaluate two leading commercial models: Gemini 2.0 Flash (Gemini Team, 2025) and GPT-4o (OpenAI, 2024b). For GPT-4o, we employ the specialized Whisper-based transcription API for ASR tasks and the general audio understanding model for all other tasks, ensuring optimal performance.

3.2 Results and Insights

3.2.1 ASR Capability

We report the ASR performance of each model across different languages under English prompts in Table 5. Gemini 2.0 Flash has the best ASR performance overall, and MERaLiON-2 has the best performance amongst open-source models. The instruction-tuned Qwen3-Omni model is also highly competitive, achieving the best results on several languages, including Vietnamese, Indonesian, and Thai. We note that state-of-the-art performance on Tamil and Burmese is particularly low at more than 0.25 WER and CER, respectively.

3.2.2 Speech Processing and Paralinguistics

Tables 6 and 7 present the results of additional speech processing and paralinguistic tasks. Results are reported under both English and SEA prompts. We observe performance deficiencies in ST where none of the open-source models achieved BLEU scores above 20. For paralinguistics tasks, emotion recognition is especially challenging. Apart

Table 5: **English-prompt ASR results averaged by language.** The performance is reported as CER for languages without explicit word boundaries and WER otherwise (2.3). Lower is better.

Model	Size	en	tl	vi	id	ta	th	zh	km	lo	ms	my
Gemma-3n-it	2B	1.32	0.42	3.77	0.17	1.20	3.03	1.55	3.92	1.42	1.06	2.81
Qwen2.5-omni	3B	**0.07**	0.60	0.27	0.15	1.36	0.12	**0.05**	2.97	1.39	0.23	2.01
MERaLiON-2	3B	**0.07**	0.20	0.35	0.11	0.43	0.08	0.11	1.72	0.86	0.17	1.19
Voxtral	3B	0.21	2.40	0.93	0.36	1.20	0.57	0.45	1.72	1.29	0.76	5.05
Gemma-3n-it	4B	0.76	0.24	2.71	0.51	0.45	0.32	0.69	1.71	**0.15**	1.98	2.98
SeaLLMs-Audio	7B	0.38	1.03	0.44	0.28	1.52	0.05	0.34	1.07	1.01	0.61	1.20
Phi-4	5.6B	0.09	5.10	2.92	2.76	1.93	2.98	0.10	3.11	2.45	3.15	2.13
Qwen2-Audio-it	7B	0.14	1.88	1.03	0.74	1.48	1.21	0.21	1.08	1.08	1.02	1.17
Qwen2.5-omni	7B	**0.07**	0.55	0.25	0.10	1.34	0.54	**0.05**	3.08	2.63	0.50	5.49
Kimi-Audio	7B	0.25	3.42	15.86	0.58	4.46	2.60	**0.05**	5.27	4.52	5.92	7.99
MERaLiON-2	10B	**0.07**	**0.18**	0.23	0.09	**0.38**	0.10	0.09	**0.77**	0.39	**0.13**	**0.83**
Qwen3-omni-Thinking	30B	0.11	0.51	0.20	0.06	0.86	0.04	0.13	5.71	1.06	0.29	7.21
Qwen3-omni-it	30B	0.09	0.42	**0.19**	**0.05**	0.44	**0.03**	0.06	1.78	0.49	0.29	2.27
Gemini 2.5 Flash	-	**0.11**	**0.13**	**0.12**	**0.03**	**0.27**	**0.05**	0.18	**0.13**	**0.16**	**0.11**	**0.31**
GPT-4o	-	0.13	0.14	0.21	0.05	0.41	0.06	**0.09**	0.30	0.38	0.17	0.66

from Kimi-Audio, no model achieved scores above 25. Even the best-performing Kimi-Audio did not score above 50.

Table 6: Results on speech processing tasks (ST, SQA) under English and SEA prompt respectively.

Model	Size	ST		SQA	
		ENG	SEA	ENG	SEA
Gemma-3n-it	2B	8.97	8.72	73.35	56.06
Qwen2.5-omni	3B	7.60	6.27	78.42	73.14
MERaLiON-2	3B	7.56	7.42	66.68	60.19
Voxtral	3B	**19.98**	18.15	82.32	79.06
Gemma-3n-it	4B	10.98	13.58	79.24	78.89
Phi-4	5.6B	3.04	0.32	64.69	47.36
SeaLLMs-Audio	7B	10.74	10.11	76.42	78.38
Qwen2-Audio-it	7B	4.54	3.20	65.82	57.95
Qwen2.5-omni	7B	7.91	8.06	71.60	75.57
Kimi-Audio	7B	3.36	7.71	69.62	63.49
MERaLiON-2	10B	17.75	**19.52**	82.00	82.05
Qwen3-omni-Thinking	30B	12.97	11.95	84.93	85.28
Qwen3-omni-it	30B	15.28	13.55	**85.77**	**85.62**
Gemini 2.5 Flash	–	16.86	18.89	**92.28**	**86.21**
GPT-4o	–	**21.24**	**21.39**	86.66	82.44

Table 7: Results on paralinguistic tasks (AgeR, ER, GR, SpkR) under English and SEA prompt respectively.

Model	Size	AgeR		ER		GR		SpkR	
		ENG	SEA	ENG	SEA	ENG	SEA	ENG	SEA
Gemma-3n-it	2B	65.91	38.76	12.21	13.17	27.71	14.65	42.35	39.32
Qwen2.5-omni	3B	50.50	34.47	13.45	9.95	36.12	20.19	28.59	17.79
MERaLiON-2	3B	68.20	46.46	23.99	18.73	48.59	46.35	39.75	33.71
Voxtral	3B	75.71	52.61	10.62	5.35	27.65	9.89	42.90	36.09
Gemma-3n-it	4B	**69.68**	58.74	12.46	13.93	53.36	27.23	39.88	39.72
Phi-4	5.6B	43.45	41.98	20.87	9.20	44.21	32.60	23.27	27.48
SeaLLMs-Audio	7B	63.16	11.64	12.34	9.17	54.97	43.66	53.59	34.37
Qwen2-Audio-it	7B	20.21	23.13	24.47	19.36	92.25	66.31	49.85	36.56
Qwen2.5-omni	7B	20.15	23.13	16.33	10.45	50.46	34.58	14.63	11.44
Kimi-Audio	7B	47.91	48.42	**36.86**	**42.55**	90.97	79.23	54.16	**48.16**
MERaLiON-2	10B	66.24	57.31	18.73	20.34	59.93	46.28	53.25	46.12
Qwen3-omni-Thinking	30B	60.81	62.25	15.06	10.34	95.00	83.78	58.78	45.41
Qwen3-omni-it	30B	63.53	**65.83**	15.94	11.31	**95.93**	**84.08**	**61.95**	46.89
Gemini 2.5 Flash	–	76.00	**79.40**	**19.50**	16.79	**92.50**	**90.06**	**71.13**	**71.75**
GPT-4o	–	**76.60**	61.20	17.00	**19.50**	46.13	31.63	10.50	8.38

3.2.3 Temporal Reasoning

In this section, we provide detailed analysis of temporal reasoning capabilities, stratifying performance across four duration bins: [0,30), [30,60), [60,120), [120,180) seconds as shown in Table 8a. Figure 8b presents coverage (C), purity (P), and F_1 of TLoc task across audio-duration ranges, using MERaLiON-2-10B as a case study.

Metrics Analysis. First, we observe systematic over-coverage in temporal reasoning across models. Notably, the instruction-tuned Qwen3-Omni model achieves exceptionally strong TCQ performance across all duration bins, substantially outperforming other models in WER/CER. In TCQ, models frequently produce content that extends beyond the queried time window. In TLoc, as demonstrated in Figure 8b, coverage consistently exceeds purity across all durations, which is a pattern we observe in most evaluated models. This asymmetry indicates weak temporal boundary localization and alignment, reflecting a recall-seeking strategy that favors longer spans, and thus higher coverage, at the cost of precision. These motivate finer-grained temporal grounding, boundary-aware training objectives, and decoding constraints that penalize span over-coverage.

Constraints on Audio Length. As shown in Table 8a, only a select subset of models sustains inference availability across all duration bins. Among open models, Voxtral, Kimi-Audio, and MERaLiON-2-10B demonstrate consistent availability, while commercial models handle the full range. Meanwhile, both TCQ and TLoc exhibit performance degradation with increasing duration: errors accumulate over longer contexts, manifesting as boundary drift and truncation, exposing current architectural limits in context window, frame compression, and long-range memory.

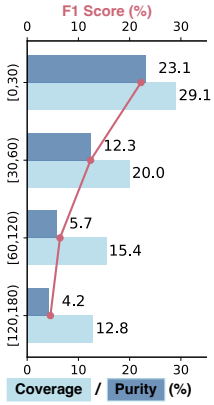
These findings underscore that temporal grounding represents an unresolved challenge in current

Table 8: Temporal reasoning performance by duration.

(a) **English-prompt TCQ and TLoc results (%) by duration.** A dash (–) indicates audio lengths for which the model is unable to perform inference.

Model	Size	TCQ (WER/CER ↓)				TLoc (F1 Score ↑)			
		0–30 s	30–60 s	60–120 s	120–180 s	0–30 s	30–60 s	60–120 s	120–180 s
SeaLLMs-Audio	7B	5.48	-	-	-	11.57	-	-	-
Qwen2-Audio-it	7B	5.56	-	-	-	33.30	-	-	-
Qwen2.5-omni	3B	8.74	9.20	-	-	30.49	18.21	-	-
Gemma-3n-it	2B	7.32	7.49	-	-	11.82	8.27	-	-
Gemma-3n-it	4B	6.76	7.38	-	-	13.25	8.72	-	-
Phi-4	5.6B	20.67	14.90	16.25	-	12.97	6.25	3.64	-
MERaLiON-2	3B	4.77	8.21	11.27	-	18.82	10.28	5.14	-
Qwen2.5-omni	7B	5.49	6.58	9.85	-	**35.74**	**19.98**	**11.32**	-
Kimi-Audio	7B	14.00	19.07	24.04	42.78	14.49	8.61	3.70	3.00
Voxtral	3B	4.74	7.74	12.86	22.13	17.85	9.87	3.71	2.45
MERaLiON-2	10B	5.12	9.48	14.72	17.67	22.22	12.37	6.40	4.53
Qwen3-omni-Thinking	30B	1.28	1.35	2.17	3.12	10.80	5.76	2.32	1.96
Qwen3-omni-it	30B	**1.18**	**1.22**	**1.34**	**1.86**	11.40	5.90	2.43	1.28
Gemini 2.5 Flash	-	**2.41**	**2.64**	**9.44**	**4.09**	11.66	7.70	5.57	5.30
GPT-4o	-	5.06	6.82	7.38	8.59	**26.47**	**17.83**	**8.53**	**5.38**

(b) TLoc metrics for MERaLiON-2-10B.



audio-language architectures, with this deficiency becoming critically pronounced in long-form audio contexts where existing architectures prove inadequate for practical deployment.

3.2.4 Effect of Prompt Language

We systematically investigate how prompt language choice: English versus native SEA language, affects model performance across our benchmark.

Figure 3 demonstrates a cross-linguistic hierarchy in prompt sensitivity. We define a Prompt Advantage Score (PAS) to quantify this effect, with its detailed formulation provided in Appendix C. Higher PAS values indicate stronger local language prompt advantage, while negative scores suggest English prompt superiority for that particular language. Indonesian emerges as the sole language showing consistent local prompt advantage (+0.3), while English and Chinese exhibit near-neutral behavior (0.0, -0.2). The remaining SEA languages display increasing English preference across two distinct clusters: moderate disadvantages for Filipino, Vietnamese, Malay, Thai, and Myanmar (ranging from -1.7 to -5.3), and severe English advantages for Lao, Tamil, and Khmer (-8.7 to -20.8).

Prompt-language performance differences in speech–text models cannot be fully explained by their text-based language understanding. To separate text-only cross-linguistic effects from cross-modal behavior, we conducted a prompt-only sanity check on the Age Recognition templates in ta, th, vi, and zh. Specifically, we ask each model (i) to translate the prompt into English and (ii) to state in one sentence what output is required, the results are shown in Table 9. For MERaLiON2-10B, it answers 8/8 correctly for both requests across

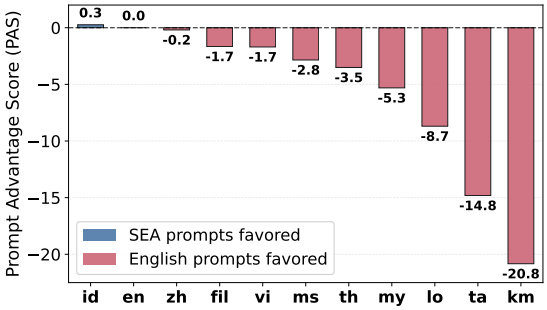


Figure 3: Cross-linguistic prompt sensitivity measured by Prompt Advantage Score (PAS).

ta/th/vi/zh. However, despite this perfect prompt comprehension in isolation, the model still shows a non-trivial gap between native-language prompts and English prompts on Age Recognition. This indicates that, for some languages and tasks, the observed prompt asymmetry cannot be attributed solely to discrepancies in language understanding, and instead points to a broader cross-modal instruction-following or alignment gap under non-English prompts.

Prompt Language	Δ Score (English − Native)	Prompt Check Failure Rate
Tamil (ta)	16.79	0
Thai (th)	15.62	0
Vietnamese (vi)	8.89	0
Chinese (zh)	3.40	0

Table 9: Performance gap on the AgeR task between English and SEA language prompts. Prompt Check Failure Rate measures the fraction of prompts where the model failed a text-only comprehension check.

3.2.5 Refusal Behavior

From Table 7, GPT-4o attains only 10.50% accuracy on speaker recognition. Inspecting the error breakdown shows that these "errors" are refusals rather than wrong predictions. As illustrated in

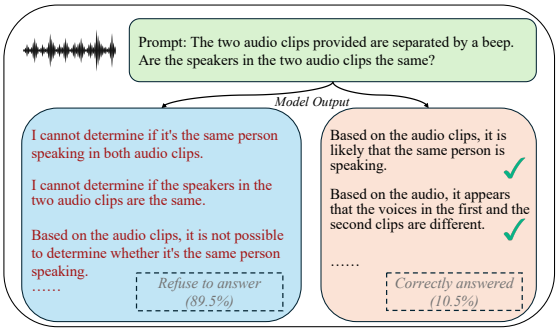


Figure 4: Speaker recognition failure examples in GPT-4o responses.

Figure 4, GPT-4o refuses to answer 89.5% of the queries. When the model does answer for 10.5% of the queries, it is consistently correct (non-refusal accuracy = 100%). This pattern emerges on our self-constructed SpkR dataset, which is likely out-of-distribution for GPT-4o. We hypothesize that the high refusal rate may stem from built-in safety policies against speaker identification, which the model treats as a privacy-sensitive task. This is consistent with the fact that when GPT-4o does answer, its non-refusal accuracy reaches 100%, suggesting deliberate abstention rather than task incomprehension. By contrast, Qwen2.5-Omni-7B also attains low SpkR performance with frequent refusals, but its accepted responses contain nontrivial mistakes, pointing to weaker calibration and label grounding rather than abstention alone.

4 Related Works

Audio/Multimodal LLMs. Recent language models have evolved to process spoken audio alongside text through diverse architectural approaches. Early work established key paradigms: alignment-based models (Tang et al., 2024; Zhang et al., 2023; Wu et al., 2023) connect speech encoders to LLMs via lightweight adaptors, while unified decoders (Rubenstein et al., 2023; Nguyen et al., 2024) share token spaces for joint speech-text modeling. Contemporary systems demonstrate varied innovations: Phi-4 (Microsoft, 2025) employs mixture-of-LoRAs for multimodality, Qwen2.5-Omni (Xu et al., 2025a) advances temporal understanding through time-aligned position encoding, and Voxtral (Voxtral Team, 2025) handles extended recordings up to 40 minutes without separate ASR. Commercial systems like GPT-4o (OpenAI, 2024b) and Gemini (Gemini Team, 2025) provide end-to-end audio understanding within unified frameworks. For Southeast Asian languages, MERaLiON (MERaLiON Team, 2024) targets Singapore's multilingual context while SeaLLMs-Audio (Liu et al., 2025) extends capabilities to five major SEA languages. However, these efforts remain limited in scope, overlooking lower-resource languages and lacking comprehensive evaluation frameworks for the region's full linguistic diversity.

Audio/Multimodal LLM Benchmarks. Audio-language evaluation has evolved from basic speech recognition to comprehensive multimodal assessment. Early efforts like SUPERB (Huang et al., 2024) aggregated speech tasks universally, and newer works (Wang et al., 2024; Yang et al., 2024) emphasize instruction-following across diverse audio types. Advanced benchmarks (Sakshi et al., 2024; Kumar et al., 2025) introduce complex reasoning with extended audio. Specialized evaluations target instruction-following (Gao et al., 2025) and domain-specific tasks (Ma et al., 2025). However, existing benchmarks remain predominantly English-centric with minimal Southeast Asian language coverage, creating a significant evaluation gap for low-resource linguistic contexts. This bias fundamentally limits understanding of model performance across the global linguistic landscape where inclusive deployment is most critically needed.

5 Conclusion

We present SEA-SPEECHBENCH, the first comprehensive benchmark for evaluating speech understanding across 11 Southeast Asian languages, comprising 97,000+ samples across 9 tasks in speech processing, paralinguistics, and temporal understanding. Our standardized framework enables reproducible, cross-linguistic comparisons through unified normalization and bilingual prompting.

Evaluation of leading commercial and open-source systems exposes systematic weaknesses: performance collapses on long audio (temporal brittleness), English prompts consistently outperform native languages (linguistic inequity), and tasks such as temporal reasoning, emotion recognition, and speech translation remain far below usability thresholds. These findings underscore persistent scalability and generalization gaps. By surfacing these limitations, SEA-SPEECHBENCH seeks to establish a rigorous baseline for developing temporally robust, linguistically inclusive, and practically deployable speech technologies for Southeast Asia's diverse communities.

6 Limitations and Risks

Data availability remains a key limitation of this work. Despite extensive efforts to collect and curate data from diverse public and community-driven sources, coverage of certain dialects and task categories remains limited due to the fundamental scarcity of high-quality, annotated resources. This constraint restricts the breadth of dialectal and task-level evaluation that can be reliably supported. Future work may explore data-efficient learning paradigms, weakly supervised or synthetic data generation, and collaborative data collection initiatives to further extend coverage across underrepresented dialects and tasks.

Risk of test set contamination is another limitation. This risk is inherently difficult to control because most evaluated models are with undisclosed training data and curation pipelines.

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A Dataset Catalog

Table 10 lists the source datasets used in our SEA-SpeechBench, along with their tasks, languages, audio lengths and licensing information.

B Data Processing and Synthesis

We provide additional details on data processing and the construction of new datasets from source materials.

B.1 Data Processing

Audio and Prompt Standardization: All audio was resampled to 16 kHz for consistency and model compatibility. We provide parallel prompts in native SEA languages and English to reflect realistic usage patterns, constructing standardized templates where needed. Prompt examples are provided in the Appendix E.

Dataset Sampling: 1. We adopted official test splits when available or sampled 1,000 instances while preserving identifiers to prevent contamination. 2. For our evaluation set, we further sampled 1,000 instances per dataset using class-balanced sampling for classification tasks, ensuring computational feasibility while maintaining representativeness. 3. We checked that uniquely identifying information such as names were removed when

Table 10: Overview of datasets: Dataset statistics, including language coverage, task types, basic audio properties, and licensing information. *Including long audios (>30s).

	Languages	Tasks	Total L (hr)	Min L (s)	Max L (s)	License
Commonvoice (Ardila et al., 2020)	zh, vi, th, id, ta, en	GR, AGE, ASR	22.66	0.58	20.78	MPL 2.0
FLEURS (Conneau et al., 2022)	zh, vi, th, my, ms, lo, km, id, tl	ASR, ST, GR	57.79	3.06	30.00	CC-BY 4.0
OpenSLR (Sodimana et al., 2018) (He et al., 2020; Oo et al., 2020)	ta, my, km	GR, ASR	6.33	1.71	17.15	CC-BY-SA 4.0
Bloom-Speech (Leong et al., 2022)	tl, my, en	ASR	0.84	0.47	29.46	CC BY-NC 4.0
Thai Elderly Speech (Lovenia and et al., 2024)	th	ASR, GR, SpkR	5.66	2.04	27.06	CC-BY-SA 4.0
LOTUS (Chotimongkol et al., 2009)	th	ASR	1.22	1.84	29.78	CC-BY-NC-SA 4.0
THAI SER (Lovenia and et al., 2024)	th	SpkR, GR, ER	6.22	0.60	29.86	CC-BY-SA 4.0
SG Streets (Khassanov et al., 2019)	en	TLoc, TCQ, SQA, ASR, GR	6.55	0.80	59.97	NA
VietMed (Pham et al., 2023)	vi	ASR	1.74	2.00	12.00	MIT
VoxVietnam-O (Vu et al., 2025)	vi	SpkR	2.43	1.42	29.68	CC
Bud500 (Pham et al., 2024)	vi	ASR	0.71	1.01	5.48	Apache-2.0
Vietnam-Celeb (Pham et al., 2023)	vi	GR	2.14	0.84	29.66	CC-BY-4.0
ASR-SMalDuSC (Lovenia and et al., 2024)	ms	ASR, SpkR, GR	8.51	2.64	29.22	CC BY-NC-ND 4.0
ASR-MALCSC (Magic Data Technology, 2025)	ms	ASR	0.74	0.61	18.16	CC BY-NC-ND 4.0
IndoWaveSentiment (Bustamin et al., 2024)	id	GR, ER	0.52	3.00	3.80	CC-BY-4.0
EmoTa (Thevakumar et al., 2025)	ta	SpkR, GR, ER	2.90	1.06	9.79	EACL
SFDUSC (Magic Data Technology, 2023)	tl	SpkR, GR, ASR	4.86	2.03	21.49	CC BY-NC-ND 4.0
YODAS2* (Li et al., 2023)	en, id, zh, th, vi	TLoc, TCQ, SQA	493.12	20.01	180.00	CC-BY 3.0
ESD (Zhou et al., 2022)	en, zh	ASR, ER, SpkR	6.56	1.41	10.79	MIT
M3ED (Zhao et al., 2022)	zh	ER, GR	0.83	0.12	7.04	CC BY-NC-ND 4.0
MIG (Myanmar Innovative Group, 2025)	my	ASR, SpkR	1.50	0.80	21.39	NA
TEC (Thanushs25, 2024)	ta	ER	0.68	2.69	29.86	NA
ASR-SgpCCSC (Magic Data Technology)	zh	ASR	43.76	0.88	180.00	CC BY-NC-ND 4.0

curating and processing data from open-source materials. We also applied profanity and content filtering on raw speech transcripts in the YODAS2 dataset.

This standardized processing transforms diverse datasets into a unified, reproducible benchmark supporting consistent evaluation across models.

B.2 New Evaluation Data Construction

SpkR (Speaker Recognition): We constructed datasets by sampling and concatenating pairs of audio segments, separated by a short beep, drawn either from the same speaker or from different speakers, to create controlled instances for the speaker verification task. Refer to Table 10 for the datasets used to synthesize the speaker recognition task.

SQA (Spoken Question Answering): We carefully filtered the YODAS2 dataset (Xinjian et al., 2023) using CTC forced alignment scores between the audio clips and the provided transcriptions with a log-probability threshold of -1, exact language match between the audio and text transcription, as well as profanity and content filtering. Based on the cleaned transcriptions, we generated question–answer pairs using GPT-4.1 (OpenAI, 2024b).

TCQ (Timestamped Content Query): We filtered the YODAS2 dataset following the same procedure used for SQA. We then identified utterances whose CTC log-probability exceeded -0.1, recording their start and end timestamps. The task was formulated such that models are required to transcribe utterances occurring between the specified timestamps.

TLoc (Temporal Localization): We adopted the same preprocessing procedure as in TCQ. The task was formulated such that models are required to predict the start and end timestamps corresponding to specified utterances.

In all cases, we applied the same standardized audio preprocessing, sample selection, and prompt construction pipeline, ensuring these synthesized datasets are consistent and compatible with the broader benchmark.

C Definition of Prompt Advantage Score (PAS)

We quantify prompt-language effects with a scale-invariant score capturing both *magnitude* and *direction*. Let s_{SEA} and s_{EN} denote task scores for SEA language prompt and English prompt, respectively. For each model M, task T, and language L, define the symmetric relative difference

$$d_{M,T,L} = \frac{\left| s_{\text{SEA}} - s_{\text{EN}} \right|}{\frac{|s_{\text{SEA}}|+|s_{\text{EN}}|}{2} + \varepsilon}, \tag{1}$$

and aggregate across models within task by the median $\tilde{d}_{T,L} = \text{median}_M \, d_{M,T,L}$. Directionality is encoded by the model-wise win rate of local prompts $w_{T,L} = \mathbb{P}_M\big(s_{\text{SEA}} > s_{\text{EN}}\big)$. The task-level Prompt Advantage Score combines direction and

effect size:

$$\mathrm{PAS}_{T,L} = \big(2(w_{T,L} - 0.5)\big) \cdot \tilde{d}_{T,L}, \qquad (2)$$

so $\mathrm{PAS}_{T,L} > 0$ favors local prompts and $\mathrm{PAS}_{T,L} < 0$ favors English. The language-level score averages over the tasks covered by L, denoted $\mathcal{T}(L)$:

$$\mathrm{PAS}_L = \frac{1}{|\mathcal{T}(L)|} \sum_{T \in \mathcal{T}(L)} \mathrm{PAS}_{T,L}. \qquad (3)$$

By construction, $|\mathrm{PAS}_L|$ measures the strength of prompt sensitivity while $\mathrm{sign}(\mathrm{PAS}_L)$ indicates the preferred prompt language.

For tasks where lower scores indicate better performance (ASR and TCQ, measured by WER/CER), we first transform the raw scores via $s \leftarrow \frac{1}{1+s}$ before computing $d_{M,T,L}$ and $w_{T,L}$, mapping the metric into a higher-is-better scale on $(0, 1]$. This ensures that $s_{\text{SEA}} > s_{\text{EN}}$ consistently corresponds to SEA prompts yielding better performance, and $\mathrm{PAS}_{T,L} > 0$ uniformly indicates local prompt advantage regardless of the original metric direction.

D Postprocessing of Evaluation

To ensure fair and consistent evaluation across Southeast Asian languages, we design a unified text normalization pipeline comprising three sequential stages:

Canonical Form Conversion. Transcripts undergo initial standardization through NFC Unicode normalization and systematic lowercasing to eliminate encoding inconsistencies and case variations. Configurable punctuation filtering preserves linguistically meaningful characters (hyphens, apostrophes) while removing extraneous symbols that could introduce evaluation noise.

Content Filtering and Lexical Standardization. Non-linguistic artifacts including speaker tags, bracketed annotations, and conversational fillers are systematically removed. Digital content undergoes targeted normalization, and English contractions receive consistent expansion. For character-based writing systems, e.g., Chinese and Thai, inter-character spacing is inserted to enable reliable tokenization.

Language-Specific Enhancement and Validation. We collaborated with native speakers across all SEA languages to validate and refine normalization heuristics.

E Evaluation Prompt Examples

We evaluate using parallel prompts in native SEA languages and English. Prompt examples are provided in Figure 5 and 6.

Figure 5: Overview of prompt examples: illustrative prompts provided for ASR, ST, SQA, AgeR, and ER tasks across multiple languages.

Tasks	Prompt Language	Input Example	Answer Example
Automatic Speech Recognition	**ENG**	**Text:** Please help me transcribe the speech into text in English.🗣: **[English Speech]**	🤖: Activity. Draw a picture of you playing a sport.
		Text: Listen to the speech and provide the text version in Malay.🗣: **[Malay Speech]**	🤖: Angin kencang, hujan batu, pemendakan berlebihan dan kebakaran hutan adalah bentuk dan kesan cuaca yang teruk. Begitu juga ribut petir, tornado, semburan air dan siklon.
	SEA	**Text:** Sila bantu saya transkripsikan ucapan ini ke dalam bentuk teks dalam Bahasa Melayu. 🗣: **[Malay Speech]**	🤖: Angin kencang, hujan batu, pemendakan berlebihan dan kebakaran hutan adalah bentuk dan kesan cuaca yang teruk. Begitu juga ribut petir, tornado, semburan air dan siklon.
		Text: กรุณาช่วยถอดเสียงพูดนี้เป็นข้อความในภาษาภาษาไทยด้วยค่ะ 🗣: **[Thai Speech]**	🤖: มันเกิดอุบัติเหตุที่ทำงาน ทำให้อูฐเกือบฆ่าคนเฝ้าประตู
Speech Translation	**ENG**	**Text:** Please help me translate the speech into text in English 🗣: **[Malay Speech]**	🤖: The television reports that the white smoke seen is from plants.
		Text: Recognize the verbal content in the speech and translate it into text in English. 🗣: **[Thai Speech]**	🤖: The smaller the Rossby number, the less movement the star will have in relation to the reversal of the Earth's magnetic poles.
	SEA	**Text:** အင်္ဂလိပ် သို့ စကားပြောချက်ကို စာသားအဖြစ် ဘာသာပြန်ပေးရန် ကျေးဇူးပြုပါ။ 🗣: **[Burmese Speech]**	🤖: Strong winds, heavy rain and sleet, and lightning are forms and effects of severe weather such as thunderstorms, tornadoes, waterspouts, and cyclones.
		Text: Vui lòng giúp tôi chuyển lời nói thành văn bản bằng Tiếng Anh 🗣: **[Vietnamese Speech]**	🤖: In his writing on the presidential speech, Oliver Sacks points out how people who are unable to understand the speech due to brain damage can still accurately judge its truthfulness.
Spoken Question Answering	**ENG**	**Text:** How many housing units were scheduled to be built in Bedok under the mentioned plan? 🗣: **[English Speech]**	🤖: Sixteen thousand five hundred housing units.
		Text: What can the playback tab be used for? 🗣: **[English Speech]**	🤖: It can be used to play videos or adjust effects.
	SEA	**Text:** Untuk apa sendok diambil dalam proses mengambil air sirih merah? 🗣: **[Indonesian Speech]**	🤖: Sendok diambil agar bisa merendam semua sirih merah.
		Text: Vì sao người nói cảm thấy buồn đau và phải chôn giấu nỗi buồn đó? 🗣: **[Vietnamese Speech]**	🤖: Vì đi qua nhiều mối tình đổ vỡ mà không ai ở lại, khiến người nói cảm thấy buồn đau và phải chôn giấu nỗi buồn đó.
Age Recognition	**ENG**	**Text:** Can you guess the speaker's age based purely on their voice characteristics? Choose among these age categories: teens (10-19), adult (20-59), or senior (60-100). 🗣: **[English Speech]**	🤖: adult (20-59)
		Text: Can you estimate the speaker's age from the audio sample? Select an age category: teens (10-19), adult (20-59), or senior (60-100). 🗣: **[Thai Speech]**	🤖: Based on the audio sample, the speaker is likely in the adult (20-50) age category.
	SEA	**Text:** பேச்சை அடிப்படையாகக் கொண்டு, பேசும் நபருக்கு ஏற்ற சராசரி வயது வரம்பை வழங்க முடியுமா? தயவுசெய்து ஒரு வயது பிரிவை தேர்ந்தெடுக்கவும்: இளையோர் (10-19), பெரியோர் (20-59), அல்லது மூத்தோர் (60-100). 🗣: **[Tamil Speech]**	🤖: பெரியோர் (20-59)
		Text: จากเสียงของผู้พูด คุณคิดว่าผู้พูดอยู่ในช่วงอายุหรือกลุ่มอายุใด? กรุณาเลือกหนึ่งกลุ่มอายุจาก: วัยรุ่น (10-19), ผู้ใหญ่ (20-59), ผู้สูงอายุ (60-100) 🗣: **[Thai Speech]**	🤖: ผู้ใหญ่ (20-59)
Emotion Recognition	**ENG**	**Text:** Based on the speaker's speech patterns, what do you think they are feeling? 🗣: **[English Speech]**	🤖: The speaker's speech suggesting they might be feeling neutral.
		Text: Can you identify or describe any emotions or feelings expressed by the speaker? Answer only using one sentence. Do not explain. 🗣: **[Tamil Speech]**	🤖: happy
	SEA	**Text:** คุณสามารถระบุหรืออธิบายอารมณ์หรือความรู้สึกที่ผู้พูดแสดงออกมาได้หรือไม่? กรุณาตอบด้วยประโยคเดียวเท่านั้น ห้ามอธิบายเพิ่มเติม 🗣: **[Thai Speech]**	🤖: ผู้พูดแสดงความรู้สึกหงุดหงิด ไม่พอใจ และอารมณ์ฉุนเฉียวอย่างรุนแรง
		Text: Apa interpretasi Anda terhadap emosi yang ditunjukkan dari petunjuk emosional yang ada dalam audio? Berikan jawaban satu kalimat tentang emosi tersebut. Jangan berikan alasan. 🗣: **[Indonesian Speech]**	🤖: Emosi yang ditunjukkan adalah kepuasan.

Figure 6: Overview of prompt examples: illustrative prompts provided for GR, SpkR, TCQ, and TLoc tasks across multiple languages.

Tasks	Prompt Language	Input Example	Answer Example
Gender Recognition	ENG	**Text:** Can you identify the speaker's gender based on the audio (Male or Female)? 🗣: **[English Speech]**	🤖: male.
		Text: From the audio, can you guess the speaker's gender (Male or Female)? 🗣: **[Thai Speech]**	🤖: female.
	SEA	**Text:** ஆடியோவை அடிப்படையாகக் கொண்டு பேசும் நபரின் பாலினத்தை (ஆண் அல்லது பெண்) அடையாளம் காண முடியுமா? 🗣: **[Tamil Speech]**	🤖: ஆண்.
		Text: Dapatkah Anda membedakan jenis kelamin pembicara berdasarkan audio ini (Laki-laki atau Perempuan)? 🗣: **[Indonesian Speech]**	🤖: Laki-laki.
Speaker Recognition	ENG	**Text:** A beep sound is placed between the two audio segments. Is there a match between the identity of the speakers in the two recordings? 🗣: **[English Speech]**	🤖: Yes, the speakers are the same.
		Text: A short beep marks the break between the two audio clips. Do you think both clips feature the same speaker? 🗣: **[Burmese Speech]**	🤖: No, the speakers are different.
	SEA	**Text:** Bunyi beep diletakkan di antara dua segmen audio. Adakah terdapat padanan identiti penutur dalam kedua-dua rakaman ini? 🗣: **[Malay Speech]**	🤖: Tidak, pembesar suara berbeza.
		Text: Hai đoạn âm thanh được cung cấp được ngăn cách bởi một tiếng bíp. Liệu người nói trong hai đoạn âm thanh này có phải là cùng một người không? 🗣: **[Vietnamese Speech]**	🤖: Không, loa thì khác nhau.
TCQ	ENG	**Text:** Please help me transcribe the speech into text in English, for the audio between 21.96 and 25.54 seconds. 🗣: **[English Speech]**	🤖: The first phase of the eastern line which included aljunied.
		Text: Process the speech and provide the text output in Thai for the duration 6.07 to 9.6 seconds. 🗣: [**Thai Speech]**	🤖: การซ้อมที่ดีคุณต้องซ้อมเสมือนว่าคุณกำลังพูด
	SEA	**Text:** Nghe đoạn phát biểu và cung cấp phiên bản văn bản bằng Tiếng Việt, bao gồm phần từ 12.03 đến 16.38 giây. 🗣: **[Vietnamese Speech]**	🤖: Tính thuế cho từng cá nhân hoàn toàn tự động để nộp về từng quốc gia sở tại.
		Text: Ubah masukan ucapan menjadi transkripsi teks dalam Bahasa Indonesia. Bagian audio yang relevan adalah dari detik 15.12 hingga 20.87. 🗣: **[Indonesian Speech]**	🤖: Kemudian untuk voice setting di sini ada lagi di sini kalian bisa menambahkan untuk kecepatannya.
TLoc	ENG	**Text:** Please give me the start and end time (in seconds) of the following content in the audio clip: *80% equal to 1.38 kilograms.* 🗣: **[English Speech]**	🤖: The time interval is **[00:22:257 - 00:25:437]**.
		Text: Identify when the following content occurs in the audio by providing the start and end time in seconds: *dan sekian informasi dari saya dan kiranya bilamana ada yang ditanyakan silahkan.* 🗣: **[Indonesian Speech]**	🤖: The start and end time of the content is:\n**Start:** 00:17.060\n**End:** 00:22.259
		Text: : แจ้งช่วงเวลาที่ตรงกับเนื้อหานี้ในไฟล์เสียง (เป็นวินาที): *การออกแบบเสื้อผ้าเครื่องแต่งกาย.* 🗣: **[Thai Speech]**	🤖: [0:0:165 – 0:1:835] การออกแบบเสื้อผ้าเครื่องแต่งกาย
	SEA	**Text:** Kapan frasa ini muncul di audio? Berikan waktu mulai dan selesai dalam detik: dan sekian informasi dari saya dan kiranya bilamana ada yang ditanyakan silahkan. 🗣: **[Indonesian Speech]**	🤖: Tentu, frasa tersebut muncul pada waktu berikut:\nMulai: 17:039 detik\nSelesai: 22:189 detik

F Model-as-Judge Prompt Examples

Table 11: Model-as-Judge prompts, adopted from (Wang et al., 2024). To ensure protocol consistency, human judges followed the same evaluation instruction.

Task	Prompt
SQA	*[Question]* *{question}* *[Reference]* *{reference}* *[Model Prediction]* *{prediction}* *[Task]* *Rate the model prediction based on its alignment with the reference, focusing on accuracy and relevance to the reference. Be critical.* *Score0: The prediction repeats or rephrases the question without giving an answer.* *Score0: The prediction is refusing to give concrete results, providing something like 'cannot decide'.* *Score0: The prediction is completely misaligned, providing incorrect or irrelevant information compared to the reference.* *Score1: The prediction shows minimal alignment, often misunderstanding or providing irrelevant details unrelated to the reference.* *Score2: The prediction recognizes the topic but diverges significantly from the reference in accuracy or relevance.* *Score3: The prediction aligns with the reference generally but lacks detail or precise accuracy in some aspects.* *Score4: The prediction is mostly accurate and relevant, closely following the reference but could be clearer or more detailed.* *Score5: The prediction is highly accurate, detailed, and matches the reference perfectly, capturing its essence and detail.* *Your response should be formatted as follows: Explanation: (Provide a concise explanation of your rating, comparing the reference with the model prediction. "The reference is [XXX], while the model prediction is [YYY]. I think ...") Rating: (int)*
AgeR **ER** **GR** **SpkR**	*[Question]* *{question}* *[Reference]* *{reference}* *[Model Prediction]* *{prediction}* *[Task]* *Rate the model prediction based on its alignment with the reference, focusing on accuracy and relevance to the reference. Be critical.* *Score0: The prediction repeats or rephrases the question without giving an answer.* *Score0: The prediction is refusing to give concrete results, providing something like 'cannot decide'.* *Score0: The prediction is wrong, providing incorrect or irrelevant information compared to the reference.* *Score1: The prediction is correct, capturing or covering the meaning from the reference.* *Your response should be formatted as follows: Explanation: (Provide a concise explanation of your rating, comparing the reference with the model prediction. "The reference is [XXX], while the model prediction is [YYY]. I think ...") Rating: (int)*

G Detailed Evaluation Results

Table 12: ASR performance: results across datasets comparing English and SEA prompts. Scores are reported as raw WER and CER values without normalization; lower values indicate better performance.

Model				MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	Whisper large v3	GPT 4o Audio
size				10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	1.5B	-
Data	**Metrics**	**Lang**	**Prompt**													No Prompt	
Bloom-Speech	WER	en	ENG	0.06	0.07	0.74	0.06	0.06	0.20	0.13	0.06	0.06	0.38	0.52	0.05	0.04	0.06
			SEA	0.06	0.07	0.74	0.06	0.06	0.20	0.13	0.06	0.06	0.38	0.52	0.05	-	-
	CER	my	ENG	0.74	0.99	1.08	2.29	2.50	2.94	0.98	2.74	4.19	2.36	4.94	0.73	1.55	0.98
			SEA	0.78	0.98	1.19	4.82	9.57	3.33	1.72	1.30	3.24	6.56	8.36	0.75	-	-
	WER	tl	ENG	0.14	0.14	0.84	5.60	9.00	3.35	1.19	0.41	0.50	0.23	0.63	0.09	0.12	0.11
			SEA	0.17	0.17	1.37	3.10	4.06	2.24	3.10	0.41	1.84	0.58	1.48	0.08	-	-
Bud500	WER	vi	ENG	0.10	0.05	0.11	1.50	38.71	1.62	1.45	0.08	0.07	7.09	8.89	0.15	0.47	0.21
			SEA	0.11	0.34	0.11	3.55	28.94	3.48	2.89	0.08	0.19	6.68	7.18	0.15	-	-
Commonvoice	WER	en	ENG	0.08	0.09	0.13	0.08	0.07	0.10	0.13	0.08	0.07	0.23	0.38	0.11	0.09	0.10
			SEA	0.08	0.09	0.13	0.08	0.07	0.10	0.13	0.08	0.07	0.23	0.38	0.11	-	-
	WER	id	ENG	0.11	0.11	0.10	1.44	0.68	0.38	0.74	0.11	0.10	0.47	0.25	0.03	0.08	0.06
			SEA	0.07	0.13	0.19	1.61	0.60	0.37	0.79	0.12	0.10	0.68	1.40	0.03	-	-
	WER	ta	ENG	0.50	0.52	1.49	1.83	4.34	1.33	1.41	1.13	1.41	0.68	1.95	0.29	0.64	0.46
			SEA	0.33	0.58	1.41	3.36	2.34	1.37	1.97	1.69	1.13	2.33	2.93	0.28	-	-
	CER	th	ENG	0.16	0.1	0.05	2.35	1.38	0.53	1.31	0.14	0.76	0.51	4.30	0.03	0.07	0.07
			SEA	0.09	0.21	0.05	8.41	1.14	0.45	1.27	0.16	0.78	11.41	5.79	0.04	-	-
	WER	vi	ENG	0.46	0.56	0.48	1.25	0.86	0.78	1.34	0.49	0.48	1.10	1.07	0.09	0.45	0.14
			SEA	0.16	0.73	0.48	1.72	1.02	0.76	0.11	0.48	0.47	1.28	0.97	0.09	-	-
	CER	zh	ENG	0.12	0.14	0.10	0.13	0.07	0.47	0.24	0.06	0.05	0.80	2.62	0.24	0.18	0.11
			SEA	0.12	0.16	0.08	0.07	0.05	0.44	0.12	0.06	0.05	2.14	2.36	0.11	-	-
ESD	WER	en	ENG	0.05	0.05	0.06	0.03	0.05	0.16	0.08	0.04	0.04	0.14	0.27	0.05	0.04	0.06
			SEA	0.05	0.05	0.06	0.03	0.05	0.16	0.08	0.04	0.04	0.14	0.27	0.05	-	-
	CER	zh	ENG	0.05	0.05	0.11	0.05	0.02	0.33	0.21	0.02	0.02	0.51	1.76	0.12	0.04	0.05
			SEA	0.05	0.05	0.07	0.02	0.02	0.39	0.05	0.02	0.02	0.74	1.11	0.08	-	-
FLEURS	WER	tl	ENG	0.16	0.18	1.06	5.92	0.94	1.41	1.98	0.80	0.57	0.07	0.16	0.07	0.12	0.07
			SEA	0.16	0.22	1.15	4.34	0.60	1.01	1.65	0.89	1.83	0.17	0.18	0.08	-	-
	WER	id	ENG	0.06	0.10	0.45	4.07	0.47	0.34	0.74	0.18	0.10	0.54	0.09	0.03	0.07	0.04
			SEA	0.06	0.12	0.12	3.19	0.36	0.28	0.64	0.11	0.31	0.10	0.09	0.03	-	-
	CER	km	ENG	0.86	1.71	1.00	4.42	8.21	1.14	1.06	3.23	4.55	1.12	4.90	0.17	1.35	0.31
			SEA	0.98	1.43	2.16	2.25	4.42	0.92	1.40	11.63	4.48	2.41	7.83	0.20	-	-
	CER	lo	ENG	0.39	0.86	1.01	2.45	4.52	1.29	1.08	1.39	2.63	0.15	1.42	0.16	1.02	0.38
			SEA	0.51	0.81	1.36	1.53	6.34	1.24	1.20	1.44	1.80	1.75	2.60	0.22	-	-
	WER	ms	ENG	0.11	0.14	0.76	3.34	1.32	0.44	1.03	0.28	0.27	0.86	0.18	0.05	0.08	0.06
			SEA	0.11	0.19	0.29	2.74	0.35	0.42	0.87	0.30	0.17	0.15	0.15	0.05	-	-
	CER	my	ENG	0.79	1.19	1.10	1.85	10.20	3.62	1.07	2.62	4.43	0.15	3.16	0.13	1.16	0.44
			SEA	0.76	1.03	1.10	4.35	8.87	3.07	1.11	1.99	4.01	1.42	1.97	0.12	-	-
	CER	th	ENG	0.14	0.13	0.10	4.14	2.93	0.57	1.04	0.16	1.20	0.15	4.03	0.07	0.09	0.04
			SEA	0.11	0.22	0.10	5.40	2.45	0.49	1.14	0.15	0.95	1.42	4.73	0.04	-	-
	WER	vi	ENG	0.10	0.16	0.91	4.46	2.39	0.40	1.05	0.10	0.09	0.17	0.30	0.06	0.08	0.04
			SEA	0.08	0.26	0.16	4.11	1.53	0.34	1.42	0.11	0.09	0.19	0.32	0.04	-	-
	CER	zh	ENG	0.10	0.12	0.84	0.1	0.08	0.36	0.18	0.07	0.06	0.25	1.00	0.18	0.08	0.07
			SEA	0.10	0.11	0.84	0.07	0.08	0.35	0.10	0.07	0.06	1.00	1.00	0.09	-	-
ASR-MALCSC	WER	ms	ENG	0.21	0.26	0.79	3.82	14.23	1.30	1.77	0.21	1.01	4.86	2.81	0.26	0.31	0.42
			SEA	0.22	0.27	0.71	2.66	7.70	1.84	1.68	0.71	1.24	4.07	4.58	0.26	-	-
MIG	CER	my	ENG	1.06	1.59	1.47	2.58	12.47	8.30	1.47	1.12	9.45	8.13	1.63	0.31	2.55	0.78
			SEA	0.97	1.53	2.09	9.35	15.58	2.80	2.09	1.64	4.43	3.58	5.53	0.29	-	-
OpenSLR	CER	km	ENG	0.68	1.72	1.14	1.80	2.33	2.29	1.10	2.71	1.61	2.29	2.94	0.09	4.70	0.29
			SEA	0.88	1.74	2.18	5.91	4.64	2.80	1.13	8.42	1.70	2.89	3.92	0.30	-	-
	CER	my	ENG	0.71	0.97	1.16	1.80	6.78	5.34	1.16	1.57	3.88	1.26	1.51	0.05	2.51	0.42
			SEA	0.74	1.07	2.63	7.51	13.1	5.52	2.13	0.97	4.40	0.99	1.42	0.06	-	-
	WER	ta	ENG	0.26	0.34	1.55	2.03	4.58	1.06	1.55	1.58	1.26	0.22	0.45	0.24	2.51	0.35
			SEA	0.26	0.40	1.30	3.59	2.47	1.10	2.22	1.58	1.47	0.71	0.85	0.25	-	-
SFDUSC	WER	tl	ENG	0.24	0.27	1.20	3.77	0.31	2.44	2.48	0.59	0.59	0.42	0.48	0.23	0.25	0.24
			SEA	0.25	0.10	1.11	3.82	1.30	2.24	4.07	0.70	0.61	0.39	0.75	0.21	-	-
ASR-SgpCCSC	CER	zh	ENG	0.07	0.11	0.30	0.13	0.04	0.62	0.19	0.05	0.05	1.19	0.80	0.19	1.00	0.13
			SEA	0.07	0.09	0.21	3.82	0.04	0.71	0.21	0.05	0.04	5.55	1.77	0.12	-	-
SG Streets	WER	en	ENG	0.10	0.05	0.57	0.17	0.82	0.39	0.20	0.09	0.09	2.27	4.11	0.22	1.00	0.29
			SEA	0.10	0.05	0.57	0.17	0.82	0.39	0.20	0.09	0.09	2.27	4.11	0.22	-	-
ASR-SMalDuSC	WER	ms	ENG	0.07	0.11	0.27	2.28	2.21	0.55	0.27	0.21	0.22	0.23	0.18	0.02	1.00	0.03
			SEA	0.07	0.10	0.27	2.24	1.30	0.56	1.08	0.21	0.23	0.26	0.24	0.02	-	-
Thai Elderly Speech	CER	th	ENG	0.08	0.07	0.04	2.07	1.56	0.71	1.35	0.14	0.17	0.54	2.72	0.07	0.06	0.10
			SEA	0.08	0.22	0.04	8.38	1.16	0.75	1.32	0.20	0.12	7.46	2.63	0.05	-	-
LOTUS	CER	th	ENG	0.02	0.03	0.02	3.35	4.51	0.46	1.14	0.04	0.03	0.06	1.06	0.01	0.03	0.01
			SEA	0.02	0.12	0.03	6.51	1.37	0.50	0.03	0.04	0.03	1.25	1.17	0.03	-	-
VietMed	WER	vi	ENG	0.27	0.64	0.27	4.47	21.47	0.92	0.27	0.40	0.35	2.49	4.80	0.18	0.65	0.44
			SEA	0.28	0.49	0.27	3.23	19.44	1.48	1.56	0.40	0.26	2.71	4.07	0.19	-	-
Average			ENG	0.27	0.41	0.65	2.29	4.85	1.42	0.95	0.67	1.24	1.27	2.01	0.14	0.74	0.22
			SEA	0.27	0.43	0.74	3.39	4.30	1.45	1.20	1.11	1.08	2.28	2.50	0.14	-	-

Table 13: Age Recognition performance: results across datasets comparing English and SEA prompts. Evaluation is conducted using the Model-as-Judge metric, where higher scores indicate better performance.

Model			MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	GPT 4o Audio
Size			10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	-
Data	**Lang**	**Prompt**													
Commonvoice	en	ENG	63.10	61.00	54.10	45.35	38.00	58.10	36.90	29.30	36.90	63.60	59.45	72.00	65.00
		SEA	63.10	61.00	54.10	45.35	38.00	58.10	36.90	29.30	36.90	63.60	59.45	72.00	65.00
	ta	ENG	64.65	71.60	52.70	49.20	51.70	77.00	18.00	48.50	18.00	65.50	63.95	75.00	71.00
		SEA	47.90	16.10	1.10	16.30	14.80	38.10	19.35	7.00	19.35	38.40	17.00	77.00	62.00
	th	ENG	57.81	67.23	68.77	40.39	49.10	81.81	16.90	48.52	16.90	73.42	72.13	74.00	78.00
		SEA	42.19	51.87	1.00	53.16	63.48	61.42	0.25	43.74	0.26	68.13	49.16	85.00	53.00
	vi	ENG	73.23	66.57	63.03	34.81	55.52	85.83	6.96	58.58	6.96	71.79	66.03	86.00	86.00
		SEA	64.35	52.34	1.00	30.09	62.61	33.73	1.56	33.13	1.56	61.40	33.01	90.00	81.00
	zh	ENG	72.40	74.60	77.20	47.50	45.25	75.80	22.30	67.60	22.00	74.10	68.00	73.00	83.00
		SEA	69.00	51.00	1.00	65.00	63.20	71.70	57.60	59.20	57.60	62.15	35.20	73.00	45.00
Average		ENG	66.24	68.20	63.16	43.45	47.91	75.71	20.21	50.50	20.15	69.68	65.91	76.00	76.60
		SEA	57.31	46.46	11.64	41.98	48.42	52.61	23.13	34.47	23.13	58.74	38.76	79.40	61.20

Table 14: Emotion Recognition performance: results across datasets comparing English and SEA prompts. Evaluation is conducted using the Model-as-Judge metric, where higher scores indicate better performance.

Model			MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	GPT 4o Audio
Size			10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	-
Data	**Lang**	**Prompt**													
EmoTa	ta	ENG	8.33	15.12	6.78	21.58	15.33	8.33	23.08	7.26	14.58	8.49	8.23	12.00	8.00
		SEA	11.97	10.84	0.85	2.24	7.91	3.73	0.96	0.85	1.00	6.94	11.43	9.00	17.00
ESD	en	ENG	19.50	23.40	12.85	19.80	64.70	9.05	40.90	9.40	13.55	8.50	9.15	15.00	13.00
		SEA	19.50	23.40	12.85	19.80	64.70	9.05	40.90	9.40	13.55	8.50	9.15	15.00	13.00
	zh	ENG	16.70	19.90	7.70	17.80	71.25	5.55	34.60	15.50	18.10	10.55	11.60	14.00	7.00
		SEA	14.15	18.75	7.45	12.50	66.15	4.80	47.55	17.70	16.10	12.65	13.65	14.00	13.50
IndoWaveSentiment	id	ENG	20.00	20.67	11.67	18.33	27.83	11.00	13.33	11.33	13.33	17.00	15.83	26.00	23.00
		SEA	23.33	18.00	17.50	3.67	29.83	8.67	15.50	16.00	14.33	13.33	9.67	18.00	22.00
M3ED	zh	ENG	19.35	26.65	10.90	20.65	19.00	7.95	14.30	11.95	13.50	7.35	10.20	16.00	12.00
		SEA	23.25	23.40	13.35	13.50	23.15	0.85	19.80	18.55	19.60	13.20	10.75	16.50	14.00
TEC	ta	ENG	34.85	42.42	24.85	30.30	42.42	23.12	30.91	28.48	27.58	21.52	19.39	42.50	43.00
		SEA	36.97	20.30	1.82	3.64	21.81	6.06	2.42	1.21	1.21	31.52	27.88	35.00	47.00
THAI SER	th	ENG	12.36	19.74	11.62	17.59	17.48	9.31	14.19	10.26	13.66	13.82	11.10	11.00	13.00
		SEA	13.19	16.44	10.37	9.06	84.29	4.29	8.38	5.97	7.33	11.36	9.63	10.00	10.00
Average		ENG	22.56	26.55	15.53	22.99	35.88	14.55	26.74	15.79	19.10	17.61	16.75	23.81	19.88
		SEA	23.97	21.96	12.76	12.78	40.86	9.94	22.26	12.72	13.95	18.90	17.59	21.44	22.06

Table 15: Gender Recognition performance: results across datasets comparing English and SEA prompts. Evaluation is conducted using the Model-as-Judge metric, where higher scores indicate better performance.

Model			MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	GPT 4o Audio
Size			10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	-
Data	**Lang**	**Prompt**													
Commonvoice	id	ENG	45.20	45.30	54.90	35.80	93.50	32.00	95.20	41.20	59.30	49.60	22.20	95.00	46.00
		SEA	57.30	62.92	56.18	57.30	66.30	44.94	61.80	62.92	52.81	57.30	60.67	82.02	53.93
	ta	ENG	53.00	51.40	50.10	45.70	90.60	44.60	96.80	23.80	53.90	54.70	37.20	95.00	33.00
		SEA	40.40	46.90	0.10	7.90	57.60	13.20	7.40	0.40	4.10	12.30	17.20	92.00	35.00
	th	ENG	50.07	36.14	57.43	28.51	96.12	44.18	96.79	46.18	61.45	51.54	29.18	93.00	50.00
		SEA	23.96	53.55	49.00	28.92	89.42	3.88	96.39	32.33	67.47	19.14	2.54	91.00	40.00
	vi	ENG	24.05	18.82	83.01	34.25	94.51	50.07	95.16	42.75	49.41	38.04	33.73	90.00	26.00
		SEA	14.64	43.14	81.57	18.30	94.41	22.09	97.52	21.44	9.80	3.66	3.53	77.00	35.00
	zh	ENG	53.70	34.60	68.90	57.10	83.90	40.90	98.20	75.30	81.80	41.00	17.80	90.00	49.00
		SEA	35.50	36.50	68.90	44.70	64.50	31.40	98.40	60.90	88.90	37.95	26.60	91.00	21.00
EmoTa	ta	ENG	67.31	49.36	52.88	40.81	90.92	22.01	98.82	17.41	36.81	55.34	49.36	94.00	25.00
		SEA	48.93	47.76	0.21	8.65	75.43	10.47	2.35	1.28	2.67	11.65	9.19	94.00	33.00
FLEURS	en	ENG	58.27	67.54	39.41	62.44	97.84	8.04	99.38	44.20	30.76	52.24	26.35	97.00	78.00
		SEA	58.27	67.54	39.41	62.44	97.84	8.04	99.38	44.20	30.76	52.24	26.35	97.00	78.00
	km	ENG	56.60	31.90	72.03	29.93	99.22	38.04	78.82	33.73	43.66	48.89	11.37	99.00	62.00
		SEA	43.40	56.34	0.39	26.08	47.06	1.96	5.49	2.35	1.05	2.75	0.78	97.00	15.00
IndoWaveSentiment	id	ENG	71.67	63.67	50.33	42.00	91.33	5.33	98.33	13.00	65.00	58.00	20.00	96.00	60.00
		SEA	60.67	3.60	50.00	22.33	79.33	1.33	94.00	19.33	31.67	24.00	13.33	95.00	14.00
M3ED	zh	ENG	84.30	64.50	51.40	82.80	74.60	8.80	86.30	15.80	43.30	58.05	30.80	84.00	23.00
		SEA	70.70	80.60	53.80	72.10	78.90	6.10	78.00	11.30	78.90	45.45	24.20	81.00	12.00
OpenSLR	ta	ENG	55.30	50.50	50.30	47.00	97.50	34.00	99.10	41.10	40.50	52.00	29.10	97.00	47.00
		SEA	37.80	42.20	0.10	6.20	60.80	9.40	8.00	0.80	4.70	15.10	14.60	97.00	36.00
SG Streets	en	ENG	89.63	39.43	61.99	53.46	95.94	5.49	84.55	8.94	5.69	64.23	31.30	98.00	32.00
		SEA	89.63	39.43	61.99	53.46	95.94	5.49	84.55	8.94	5.69	64.23	31.30	98.00	32.00
ASR-SMalDuSC	ms	ENG	52.40	49.80	52.20	22.30	96.70	26.80	93.90	66.50	58.90	49.70	28.00	98.00	76.00
		SEA	44.00	50.30	45.70	37.00	94.30	19.00	61.30	23.55	15.90	34.70	20.20	96.00	24.00
Thai Elderly Speech	th	ENG	68.15	55.75	34.48	22.58	94.96	44.76	97.48	45.16	60.28	65.73	26.66	99.00	46.00
		SEA	26.92	46.47	69.56	45.67	84.68	3.33	96.98	23.99	82.01	37.40	2.42	85.00	51.00
THAI SER	th	ENG	63.46	63.87	49.21	53.40	86.81	18.32	87.54	31.10	60.00	56.86	27.23	86.00	44.00
		SEA	61.78	58.12	81.15	41.68	84.29	12.14	85.86	26.13	80.00	33.93	3.77	85.00	34.00
Vietnam-Celeb	vi	ENG	65.80	54.80	50.90	49.30	71.10	19.10	69.70	31.70	56.60	57.80	23.10	69.00	41.00
		SEA	61.40	63.50	50.30	30.30	72.80	5.00	69.30	23.00	27.50	10.65	1.60	73.00	36.00
Average		ENG	59.78	49.43	55.04	44.98	89.52	28.67	90.46	37.69	50.60	53.59	29.65	91.88	46.58
		SEA	46.93	47.33	44.40	34.05	78.47	11.95	66.05	22.70	35.65	29.00	17.36	89.59	32.94

Table 16: Speaker Recognition performance: results across datasets comparing English and SEA prompts. Evaluation is conducted using the Model-as-Judge metric, where higher scores indicate better performance.

Model			MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	GPT 4o Audio
Size			10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	-
Data	**Lang**	**Prompt**													
EmoTa	ta	ENG	53.10	43.06	56.94	14.10	57.05	46.15	50.64	26.50	13.25	39.53	41.99	71.00	6.00
		SEA	53.85	31.73	0.00	15.71	51.17	33.97	15.44	7.91	12.39	27.99	40.92	73.00	13.00
ESD	en	ENG	52.90	39.20	56.75	34.90	53.80	37.70	47.90	24.40	5.70	39.10	45.90	71.00	10.00
		SEA	52.90	39.20	56.75	34.90	53.80	37.70	47.90	24.40	5.70	39.10	45.90	71.00	10.00
	zh	ENG	53.10	43.70	49.10	24.80	48.00	42.40	51.60	31.70	23.30	41.40	41.20	59.00	12.00
		SEA	50.60	43.30	48.10	45.20	44.90	43.50	45.30	38.10	30.70	45.58	44.40	61.00	4.00
mig	my	ENG	50.00	35.15	53.50	22.50	50.90	31.50	54.60	30.60	13.50	35.90	29.40	70.00	5.00
		SEA	36.50	12.70	0.20	11.60	12.60	27.20	1.00	6.30	6.45	43.80	37.30	77.00	4.00
ASR-SMalDuSC	ms	ENG	59.20	44.50	57.80	23.20	59.30	47.00	46.60	24.00	10.80	37.40	44.00	74.00	14.00
		SEA	48.05	39.30	42.20	28.20	59.70	44.70	41.10	29.40	17.20	47.60	38.90	82.00	16.00
Thai Elderly Speech	th	ENG	52.92	38.13	52.29	20.42	52.10	50.31	48.02	29.48	14.27	42.81	43.65	75.00	6.00
		SEA	34.06	26.77	37.92	27.40	56.25	41.56	43.65	6.56	5.00	38.49	30.52	71.00	7.00
THAI SER	th	ENG	51.02	38.45	50.70	22.13	58.00	46.72	50.16	30.93	18.80	41.57	46.94	70.00	20.00
		SEA	42.96	36.84	42.86	30.08	60.47	34.80	42.11	12.24	6.20	37.16	35.02	61.00	7.00
VoxVietnam-O	vi	ENG	53.80	35.80	51.60	24.10	54.10	41.40	49.30	31.10	17.40	41.30	45.70	79.00	11.00
		SEA	50.00	39.80	46.90	26.80	46.40	25.30	56.00	17.40	7.90	38.00	41.60	78.00	6.00
Average		ENG	53.25	39.75	53.59	23.27	54.16	42.90	49.85	28.59	14.63	39.88	42.35	71.13	10.50
		SEA	46.12	33.71	34.37	27.48	48.16	36.09	36.56	17.79	11.44	39.72	39.32	71.75	8.38

Table 17: Speech Translation performance: results across datasets comparing English and SEA prompts. Evaluation is based on the BLEU metric, where higher scores indicate better performance.

Model			MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	GPT 4o Audio
Size			10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	-
Data	**Lang**	**Prompt**													
FLEURS	id	ENG	32.48	20.97	25.55	0.70	10.75	35.02	9.37	16.65	16.55	21.40	20.52	24.07	33.44
		SEA	30.02	21.98	25.97	0.13	16.81	34.58	6.23	11.15	17.93	24.80	17.57	24.43	34.90
	km	ENG	2.19	0.50	0.73	0.23	0.35	7.04	0.47	0.26	0.48	4.72	2.52	12.40	6.34
		SEA	1.97	0.45	0.33	0.05	0.49	0.08	0.11	0.27	0.24	4.71	2.50	13.76	7.52
	lo	ENG	11.34	1.03	5.91	0.04	0.55	10.44	0.47	2.49	3.06	7.66	6.75	15.36	13.61
		SEA	12.09	0.88	1.04	0.01	1.04	0.55	0.11	0.80	2.35	8.94	7.18	15.04	13.06
	ms	ENG	31.04	15.52	19.71	1.04	6.15	30.44	5.25	12.16	13.19	18.24	16.41	26.49	33.53
		SEA	34.35	13.09	20.30	0.22	20.02	30.33	2.57	10.12	14.24	23.04	14.37	23.70	33.93
	my	ENG	0.37	0.12	0.29	0.11	0.03	0.73	0.40	0.11	0.35	0.78	0.35	8.59	1.47
		SEA	0.59	0.14	0.03	0.11	0.04	0.63	0.14	0.02	0.10	0.73	0.10	15.05	2.08
	th	ENG	17.22	3.47	12.30	0.14	2.42	19.53	0.47	7.90	8.34	12.95	9.57	16.93	22.41
		SEA	18.70	5.59	11.51	0.02	3.52	20.15	0.55	7.86	9.29	14.90	8.49	20.25	22.93
	tl	ENG	25.79	8.28	1.67	0.92	5.99	30.42	1.68	2.52	2.50	17.14	12.98	14.50	28.48
		SEA	27.22	7.76	1.76	0.10	23.27	30.69	1.25	0.89	2.29	22.47	14.44	16.09	26.20
	vi	ENG	19.18	6.50	13.52	0.12	3.94	24.79	2.05	11.40	12.02	7.19	4.89	17.26	27.10
		SEA	22.91	5.95	13.00	0.01	4.19	25.05	1.91	10.31	12.32	11.84	7.51	19.74	30.27
	zh	ENG	20.14	11.63	17.01	24.08	0.01	21.36	20.69	14.89	14.73	8.72	6.75	16.18	24.77
		SEA	20.74	10.94	17.11	2.28	0.01	21.30	15.88	15.02	13.81	10.78	6.37	21.91	21.60
Average		ENG	17.75	7.56	10.74	3.04	3.36	19.98	4.54	7.60	7.91	10.98	8.97	16.86	21.24
		SEA	18.73	7.42	10.11	0.32	7.71	18.15	3.20	6.27	8.06	13.58	8.72	18.89	21.39

Table 18: TCQ performance: results across datasets comparing English and SEA prompts. Scores are reported as raw WER and CER values without normalization; lower values indicate better performance.

Model				MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	GPT 4o Audio
Size				10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	-
Data	**Lang**	**Length (Max)**	**Prompt**													
SG Streets	en	30	ENG	2.43	2.43	2.12	2.67	2.47	1.89	2.30	2.64	4.21	2.20	2.32	0.47	2.24
			SEA	2.43	2.43	2.12	2.67	2.47	1.89	2.30	2.64	4.21	2.20	2.32	0.47	2.24
		60	ENG	3.44	3.47	-	2.10	3.36	2.12	-	2.29	3.35	1.91	1.94	0.76	2.49
			SEA	3.44	3.47	-	2.10	3.36	2.12	-	2.29	3.35	1.91	1.94	0.76	2.49
ASR-SgpCCSC	zh	30	ENG	4.78	5.44	6.54	5.48	9.94	6.84	9.08	3.91	3.69	8.84	9.55	1.57	5.17
			SEA	4.34	5.13	5.68	4.07	10.43	5.46	8.87	4.15	2.91	8.62	9.67	1.57	4.99
		60	ENG	9.85	11.28	-	6.72	22.74	12.86	-	3.85	5.73	9.98	9.36	1.89	8.00
			SEA	9.50	10.25	-	4.03	20.95	8.16	-	3.77	3.71	9.08	8.83	1.89	9.21
		120	ENG	20.93	21.15	-	18.92	41.07	27.07	-	-	18.59	-	-	3.10	8.68
			SEA	20.86	17.09	-	14.94	37.36	12.12	-	-	8.19	-	-	3.10	10.81
		180	ENG	20.59	-	-	-	57.41	36.85	-	-	-	-	-	3.30	7.35
			SEA	21.81	-	-	-	56.92	16.92	-	-	-	-	-	3.30	9.04
YODAS2	en	30	ENG	5.34	5.31	3.81	4.53	5.79	3.62	4.57	4.94	4.42	5.03	5.03	1.36	4.42
			SEA	5.34	5.31	3.81	4.53	5.79	3.62	4.57	4.94	4.42	5.03	5.03	1.36	4.42
		60	ENG	10.98	10.74	-	6.39	11.76	5.48	-	7.01	4.86	5.83	5.96	1.29	6.37
			SEA	10.98	10.74	-	6.39	11.76	5.48	-	7.01	4.86	5.83	5.96	1.29	6.37
		120	ENG	16.19	15.10	-	9.02	22.28	9.09	-	-	6.92	-	-	1.82	6.49
			SEA	16.19	15.10	-	9.02	22.28	9.09	-	-	6.92	-	-	1.82	6.49
		180	ENG	-	-	-	-	-	-	-	-	-	-	-	1.75	6.72
			SEA	-	-	-	-	-	-	-	-	-	-	-	1.75	6.72
	id	30	ENG	3.82	3.70	3.42	21.41	22.32	2.71	4.05	3.76	3.23	3.78	3.81	0.64	3.18
			SEA	3.77	3.50	3.52	14.13	9.58	3.06	3.86	3.81	4.54	4.00	3.91	1.36	3.20
		60	ENG	7.88	6.44	-	14.18	19.97	4.40	-	5.26	4.09	4.23	4.30	1.21	4.47
			SEA	7.63	6.00	-	9.43	8.76	4.75	-	5.53	6.53	4.24	4.44	1.79	5.23
		120	ENG	13.07	9.45	-	13.92	16.49	7.27	-	-	6.09	-	-	1.38	4.88
			SEA	12.59	9.08	-	12.35	10.94	6.27	-		8.20	-	-	2.37	4.89
		180	ENG	14.00	-	-	-	16.24	10.26	-	-	-	-	-	2.02	5.42
			SEA	13.86	-	-	-	9.26	7.29	-	-	-	-	-	2.41	4.94
	th	30	ENG	3.82	1.49	5.31	80.08	27.81	5.24	3.14	36.29	9.68	9.21	10.49	10.15	7.09
			SEA	3.75	1.57	6.33	40.13	16.43	6.93	2.47	17.47	12.56	9.85	13.22	8.17	8.11
		60	ENG	6.05	1.77	-	51.66	37.37	8.21	-	36.06	11.39	9.79	9.80	9.32	10.31
			SEA	5.63	1.73	-	37.39	17.88	9.97	-	23.94	13.33	9.74	9.89	7.43	11.61
		120	ENG	10.10	2.10	-	41.25	32.92	12.71	-	-	11.80	-	-	10.16	11.10
			SEA	8.87	1.86	-	37.47	19.98	14.27	-		14.77	-	-	8.02	11.84
		180	ENG	10.52	-	-	-	60.78	14.44	-	-	-	-	-	12.21	12.98
			SEA	9.76	-	-	-	27.66	16.71	-	-	-	-	-	9.93	12.87
	vi	30	ENG	5.48	5.22	4.11	21.25	17.42	4.28	4.42	3.06	3.11	5.30	5.95	1.26	4.33
			SEA	5.46	4.92	4.32	14.75	19.24	4.72	4.68	3.50	5.37	5.46	6.21	1.39	4.29
		60	ENG	10.60	7.46	-	12.86	15.43	7.54	-	3.80	3.78	5.79	5.85	1.12	5.16
			SEA	10.42	6.25	-	11.12	17.28	7.88	-	3.73	6.13	5.89	5.84	1.46	5.90
		120	ENG	14.05	8.90	-	15.76	11.24	11.77	-	-	4.81	-	-	46.66	5.90
			SEA	13.95	7.34	-	19.65	23.72	11.90	-	-	6.45	-	-	2.01	5.72
		180	ENG	12.22	-	-	-	17.52	16.12	-	-	-	-	-	1.77	5.31
			SEA	12.03	-	-	-	26.28	12.47	-	-	-	-	-	2.06	4.55
	zh	30	ENG	10.16	9.83	13.04	9.29	12.21	8.61	11.38	6.57	10.10	12.95	14.12	1.41	8.99
			SEA	8.46	9.40	11.19	8.49	12.23	6.91	11.00	5.31	7.93	12.94	13.58	2.98	10.74
		60	ENG	17.60	16.31	-	10.41	22.87	13.54	-	6.15	12.89	14.16	15.26	2.86	10.92
			SEA	15.95	14.34	-	11.48	23.07	8.33	-	4.67	9.09	13.88	15.08	4.40	13.01
		120	ENG	28.66	22.18	-	14.92	44.31	22.13	-	-	20.73	-	-	2.94	14.59
			SEA	25.32	19.94	-	11.47	43.27	10.74	-	-	6.88	-	-	3.73	15.04
		180	ENG	31.04	-	-	-	61.92	33.00	-	-	-	-	-	3.51	13.76
			SEA	28.22	-	-	-	73.53	14.62	-	-	-	-	-	4.49	17.39
		180	ENG	17.67	-	-	-	42.78	22.13	-	-	-	-	-	4.09	8.59
			SEA	17.14	-	-	-	38.73	13.60	-	-	-	-	-	3.99	9.25
		120	ENG	14.72	11.27	-	16.25	24.04	12.86	-	-	9.85	-	-	9.44	7.38
			SEA	13.97	10.06	-	14.99	22.51	9.20	-	-	7.34	-	-	3.01	7.83
		30	ENG	5.12	4.77	5.48	20.67	14.00	4.74	5.56	8.74	5.49	6.76	7.32	2.41	5.06
			SEA	4.79	4.61	5.28	12.68	10.88	4.66	5.39	5.97	5.99	6.87	7.70	2.47	5.43
		60	ENG	9.48	8.21	-	14.90	19.07	7.74	-	9.20	6.58	7.38	7.49	2.64	6.82
			SEA	9.08	7.54	-	11.70	14.72	6.67	-	7.28	6.71	7.22	7.42	2.72	7.69

Table 19: TLoc performance: results across datasets comparing English and SEA prompts. Evaluation is based on the F1 score metric, where higher values indicate better performance.

Model				MERaLiON2 10B	MERaLiON2 3B	SeaLLMs Audio 7B	Phi-4 multi--modal instruct	Kimi Audio	Voxtral mini	Qwen2 Audio 7B Instruct	Qwen 2.5 Omni 3B	Qwen 2.5 Omni 7B	gemma 3n E4B-it	gemma 3n E2B-it	Gemini 2.5 Flash	GPT 4o Audio
Size				10B	3B	7B	5.6B	7B	3B	7B	3B	7B	4B	2B	-	-
Data	**Lang**	**Length (Max)**	**Prompt**													
ASR-SgpCCSC	zh	30	ENG	11.10	10.85	8.45	19.90	-	-	19.10	13.10	31.21	7.86	6.44	11.89	22.19
			SEA	11.10	10.85	8.45	19.90	-	-	19.10	13.10	31.21	7.86	6.44	11.89	22.19
		60	ENG	6.23	6.42	-	7.73	-	-	-	10.78	12.71	6.64	2.88	1.26	10.50
			SEA	6.23	6.42	-	7.73	-	-	-	10.78	12.71	6.64	2.88	1.26	10.50
		120	ENG	4.18	2.59	-	4.66	-	-	-	-	7.84	-	-	4.55	6.14
			SEA	4.18	2.59	-	4.66	-	-	-	-	7.84	-	-	4.55	6.14
SG Streets	en	30	ENG	40.28	33.56	22.56	11.96	17.17	27.70	54.85	49.61	44.77	18.04	19.18	16.62	40.25
			SEA	40.28	33.56	22.56	11.96	17.17	27.70	54.85	49.61	44.77	18.04	19.18	16.62	40.25
		60	ENG	23.75	15.16	-	5.30	11.13	17.90	-	29.78	38.05	7.36	12.87	17.90	37.94
			SEA	23.75	15.16	-	5.30	11.13	17.90	-	29.78	38.05	7.36	12.87	17.90	37.94
YODAS2	en	30	ENG	22.99	20.00	9.92	12.70	14.78	15.46	41.62	34.01	36.27	16.49	16.35	5.88	24.30
			SEA	22.99	20.00	9.92	12.70	14.78	15.46	41.62	34.01	36.27	16.49	16.35	5.88	24.30
		60	ENG	13.91	11.46	-	6.79	8.43	7.76	-	21.07	18.67	10.44	11.36	7.98	17.14
			SEA	13.91	11.46	-	6.79	8.43	7.76	-	21.07	18.67	10.44	11.36	7.98	17.14
		120	ENG	8.28	6.12	-	3.47	2.72	2.62	-	-	10.78	-	-	2.99	7.65
			SEA	8.28	6.12	-	3.47	2.72	2.62	-	-	10.78	-	-	2.99	7.65
	id	30	ENG	27.44	24.58	16.41	14.02	17.06	20.90	38.26	40.91	45.27	15.55	12.60	11.83	28.48
			SEA	26.70	18.43	19.78	10.63	15.04	18.26	37.56	21.84	34.71	20.16	16.19	16.19	30.01
		60	ENG	14.90	12.99	-	7.47	9.94	11.76	-	23.78	21.44	10.50	9.66	11.04	20.84
			SEA	14.82	10.85	-	7.66	8.15	10.77	-	12.86	0.00	14.53	11.59	15.57	22.20
		120	ENG	10.13	8.58	-	4.96	5.05	5.47	-	-	16.59	-	-	10.01	15.04
			SEA	10.43	6.45	-	5.18	4.91	4.17	-	-	13.73	-	-	9.42	15.60
	th	30	ENG	17.79	17.42	8.94	10.48	12.97	14.24	16.47	25.52	37.62	12.45	9.48	12.83	26.66
			SEA	16.04	15.32	9.16	13.75	13.02	10.84	11.92	14.08	27.42	10.71	6.93	25.73	17.62
		60	ENG	9.03	8.56	-	5.90	8.03	7.16	-	14.76	15.22	9.28	7.72	4.35	18.64
			SEA	9.92	5.08	-	7.48	5.87	6.73	-	9.77	17.20	7.36	5.62	16.38	15.51
		120	ENG	5.65	4.13	-	3.04	4.08	3.78	-	-	11.17	-	-	8.16	11.31
			SEA	5.87	1.94	-	3.70	5.80	3.00	-	-	6.75	-	-	15.81	9.18
	vi	30	ENG	22.40	14.50	8.22	10.30	15.84	18.81	35.08	33.18	39.17	12.14	10.35	10.11	25.67
			SEA	24.76	13.49	14.04	14.63	8.16	15.44	28.60	31.59	40.73	12.23	10.82	8.70	28.80
		60	ENG	12.18	11.54	-	4.29	9.76	8.86	-	17.98	24.73	9.35	9.14	6.35	11.98
			SEA	14.77	7.92	-	7.70	11.35	7.30	-	17.96	28.44	10.95	8.88	7.28	21.40
		120	ENG	6.34	7.34	-	2.44	4.84	3.76	-	-	12.73	-	-	2.83	7.40
			SEA	6.88	6.76	-	3.11	1.20	4.42	-	-	20.39	-	-	3.40	12.68
	zh	30	ENG	13.56	10.80	6.49	11.41	9.13	9.97	27.69	17.10	15.84	10.19	8.32	12.43	17.77
			SEA	12.52	10.61	6.69	11.02	11.41	11.14	26.21	13.93	16.46	12.36	7.29	10.11	14.80
		60	ENG	6.61	5.85	-	6.28	4.36	5.76	-	9.35	9.07	7.45	4.29	5.02	7.73
			SEA	6.80	7.91	-	5.62	5.80	5.61	-	8.50	11.54	6.95	7.15	4.13	4.64
		120	ENG	3.85	2.08	-	3.26	1.81	2.93	-	-	8.81	-	-	4.89	3.64
			SEA	3.98	4.38	-	3.16	0.00	2.35	-	-	4.77	-	-	6.32	4.34