

PSK at WMT 2026 MIST: Task-Specialized QLoRA Adapters for Multilingual Summarization and Question Answering

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Abstract

We describe the PSK submission to the WMT 2026 Multilingual Instruction Shared Task. Our system uses the 3.35B-parameter Tiny Aya Global model with three QLoRA adapters, one for each task. The adapters are trained on multilingual document–summary pairs, passage-based question answering, and filtered standalone question answering. The summarization data also includes scientific papers with their author-written abstracts. On our held-out split, the context and summarization adapters perform better than our multitask adapter, while results for open QA are mixed. Official evaluation ranks PSK sixth overall and fourth for summarization. Context QA and open QA remain weaker, and the multitask open-QA route outperforms both specialized open-QA adapters.

1 Introduction

The WMT 2026 Multilingual Instruction Shared Task (MIST) evaluates models under a 10B-parameter limit on three tasks: context-based question answering, summarization from a document in language X to language Y , and open-ended generation (WMT 2026 MIST Organizers, 2026). The test set covers 24 languages and contains both same-language and cross-lingual generation. MIST follows the broader multilingual evaluation effort introduced in WMT 2025, which found substantial variation across tasks and languages and also showed that automatic metrics are imperfect for open generation (Kocmi et al., 2025).

We use one multilingual backbone with three task-specific adapters. Tiny Aya Global (Salamanca et al., 2026) is first adapted to the provided data and then continued separately for each task. This design preserves a single 3.35B backbone while allowing the supervision and decoding policy to follow the output structure of each task.

2 Task and System Overview

MIST provides a task label at inference time. We use it to select one of three LoRA adapters and the corresponding decoding configuration (Figure 1); there is no language-specific routing.

2.1 Base Model and Initial Adaptation

We use CohereLabs/tiny-aya-global, a 3.35B-parameter model covering 70 languages (Salamanca et al., 2026). Its 8K context window supports the longer task inputs. An initial multitask adapter is trained on 20,293 provided examples using a deterministic 85/15 split; the resulting 3,626 held-out examples are reused for model selection. The task-specific adapters are initialized from this model.

3 Training Data

Table 1 summarizes the task-specific training data. Validation examples and exact normalized test inputs are excluded from training. Since several training sources belong to benchmark families also used by MIST, this check does not rule out paraphrased, document-level, or family-level overlap.

3.1 Summarization

The 12,000-example mixture is divided evenly between general and scientific text. General examples combine provided data with CrossSum (Bhattacharjee et al., 2023), WikiLingua (Ladhak et al., 2020), and UPDESH (Chitale et al., 2026). The scientific portion uses full ACL Anthology papers (Bird et al., 2008) with author-written abstracts. No Language Left Behind (NLLB) (NLLB Team, 2024) supplies non-English targets, which are filtered for language, length, repetition, and semantic consistency. We remove test overlaps and placeholder-heavy papers. We also screen the

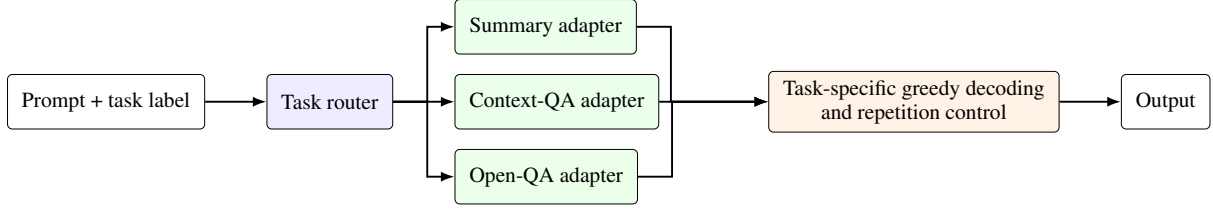


Figure 1: The three routes share one frozen Tiny Aya Global backbone. The known task label selects an adapter and its decoding policy; language does not change the route.

Adapter	Rows	Context	Main sources and construction
Multitask adapter	20,293	8,192	Provided MIST sample training split across all three tasks
Summarization	12,000	8,192	6,000 general examples from the provided data, CrossSum, WikiLingua, UPDESH, and targeted language pools; 6,000 ACL papers paired with author abstracts
Context QA	8,512	4,096	Belebele, answerable TyDi QA, MLQA, MCIF, UPDESH cultural multihop data, and small Czech/Yoruba Aya pools
Open QA	6,400	2,048	Provided open-QA examples plus filtered Aya and WMT25 MIST examples; includes Hindi questions and answers translated into Bhojpuri

Table 1: Supervised data used by the selected task adapters. Each is initialized from the multitask adapter.

provided data for likely misalignment by comparing each summary with chunks of its source document and discarding a pair only when both its best LaBSE similarity and best chrF score fall below fixed thresholds.

3.2 Context Question Answering

The context-QA training set combines Belebele (Bandarkar et al., 2024), answerable TyDi QA (Clark et al., 2020), MLQA (Lewis et al., 2020), MCIF (Papi et al., 2026), UPDESH, and small Czech and Yoruba Aya subsets. MLQA supplies parallel and cross-lingual examples.

3.3 Open-Ended Question Answering

Open QA combines provided examples, WMT25 MIST questions, and the Aya Dataset and Collection (Singh et al., 2024). We retain short factual and explanatory QA while excluding passage-dependent, multiple-choice, creative-writing, code, translation, and continuation tasks. We also translate a small set of Hindi questions and answers into Bhojpuri with NLLB.

4 Training and Inference

We use QLoRA (Detrmers et al., 2023) with 4-bit NF4 quantization and BF16 computation. LoRA (Hu et al., 2022) is applied to the attention and feed-forward projections with rank 16, alpha 32, and dropout 0.05. Each adapter is trained for one epoch with effective batch size 16; learning rates

are 1×10^{-4} for summarization, 8×10^{-5} for open QA, and 2×10^{-4} for context QA.

Inference uses greedy decoding. After observing repetitive outputs on the development set, we add repetition penalties of 1.05 for open QA and 1.03 for summarization. Repetition occurred in both open QA and summarization, but not in context QA. For open QA, the mean repeated 4-gram fraction falls from 0.110 to 0.057 and the share of outputs reaching the generation limit falls from 14.9% to 8.7%; the largest repetition problems occur in Yoruba, Turkish, Bengali, Czech, and Korean. Blocking repeated 4-grams in summarization removes all such repeats on the development set and reduces outputs reaching the limit from 9.0% to 2.0%.

5 Development Results

We report exact match (EM), chrF (Popović, 2015), ROUGE-L (Lin, 2004), and LaBSE cosine similarity (Feng et al., 2022). For open QA, we use chrF, ROUGE-L, and LaBSE together with manual inspection of validation outputs.

5.1 Untouched Model Baseline

Table 2 compares the untouched Tiny Aya Global model with the initial multitask adapter on the same 3,626 held-out examples from the provided data. This isolates the effect of the first supervised adaptation before the task-specific experiments.

Task	<i>n</i>	Metric	Untouched	Multitask
Summarization	1,315	chrF	17.25	25.79
Context QA	1,517	EM	0.00	66.25
Open QA	794	chrF	20.94	28.70

Table 2: Untouched Tiny Aya Global and the multitask adapter on the original held-out split. EM is a percentage.

5.2 Task-Level Results

Table 3 reports development scores for the evaluated adapters. The 8.5k context mixture and the 12k summary mixture are selected for submission.

The targeted context continuation is marginally higher on ROUGE-L and LaBSE, whereas the 8.5k context mixture is higher on EM and chrF. We therefore select the latter.

5.3 Scientific Summarization

Table 4 separates the 336 scientific examples from the remaining 1,315 summarization examples. Gold scientific targets are author abstracts; non-English targets are translated and quality filtered. The scientific subset accounts for approximately 87% of the aggregate chrF gain. The improvement on the non-scientific subset is much smaller.

5.4 Open QA and Submitted Systems

Best-score QA has the strongest aggregate automatic scores. Long-form QA is stronger on a manually identified set of long-form prompts and reaches the generation limit less often. Our main submission uses Long-form QA. A second submission uses Best-score QA. Table 5 summarizes the three submitted routes.

6 Official Results

PSK ranks sixth among 15 teams in the official aggregate ranking, with a mean task rank of 7.33. Table 6 shows the primary metric reported on each task sheet. Summarization is the strongest route, ranking fourth. Context QA and open QA rank tenth and seventh, respectively.

The three open-QA submissions score 62.68 (Long-form QA), 63.70 (Best-score QA), and 64.59 (multitask route) before pooling, so neither specialized open-QA adapter improves on the multitask route in the official evaluation. For summarization, the system produces the requested language in 98.1% of cases and ranks in the top five

for 18 of 24 languages, including first place for Yoruba. However, its NLI faithfulness rank is 12th and its two judge-based fluency ranks are 14th and 15th. The result therefore reflects strong reference overlap and language control, but not consistently strong fluency or faithfulness.

7 Analysis

Separate adapters improve context QA and summarization on our development set. Scientific summarization also improves after adding papers and their abstracts to the training data. Open QA has no clear winner. Best-score QA performs better on automatic metrics, while Long-form QA works better on the longer questions we checked manually and is less likely to hit the output limit.

We manually inspect the six largest open-QA chrF regressions in Marathi and the six largest in Spanish. In Marathi, most are factual errors or shorter outputs that preserve the same incorrect fact; for example, both models give the wrong year for the Buddha’s Mahaparinirvana, but the specialized output is shorter and receives a lower chrF score. In Spanish, we find both genuine failures, such as omitting part of a requested story summary, and reference effects. One continuation prompt receives a much shorter, non-repetitive answer after adaptation but a lower chrF score; another item has a Spanish prompt and system answer but an English reference wrapper. These 12 post-hoc examples show that the language-level declines mix real content errors with answer-length and reference-format effects.

The shared summarization route improves chrF over the multitask adapter in all 28 represented languages. The shared context-QA route improves exact match in 19 of 25 languages, ties in four, and declines in two. Open QA remains mixed: the primary route improves chrF in 9 of 19 languages, and variant A improves it in 10 of 19. Appendix A gives the complete language-level changes and cell sizes.

8 Conclusion

We present a routed Tiny Aya Global system with one QLoRA adapter per MIST task. PSK ranks sixth overall and fourth for summarization in the official evaluation. The summarization route has strong reference overlap and language control, although its fluency and faithfulness scores leave room for improvement. Context QA is

Task	Training variant	n	EM	chrF	ROUGE-L	LaBSE
Summarization	Multitask adapter	1,651	0.00	22.97	0.1571	0.6681
	12k general/scientific mix	1,651	0.00	26.81	0.1780	0.6919
Context QA	Multitask adapter	1,517	66.25	77.07	0.6834	0.8813
	8.5k context mixture	1,517	68.89	78.58	0.6959	0.8897
	+4.8k targeted continuation	1,517	68.36	78.36	0.6966	0.8906
Open QA	Multitask adapter	794	3.90	28.34	0.2287	0.6524
	Long-form QA	794	4.03	27.96	0.2307	0.6600
	Best-score QA	794	4.16	28.41	0.2329	0.6638

Table 3: Internal model-selection results on identical held-out rows. EM is a percentage and LaBSE is cosine similarity.

Subset	n	Multitask	12k mix	Δ chrF
Non-scientific	1,315	25.45	26.05	+0.60
Scientific	336	13.27	29.76	+16.49
All	1,651	22.97	26.81	+3.84

Table 4: Stratified summarization chrF. The 12k mixture is evenly divided between general and scientific training data.

System	Summary	Context	Open
PSK-primary	12k mix	8.5k mix	Long-form
PSK-variant_A	12k mix	8.5k mix	Best-score
PSK-variant_B	12k mix	8.5k mix	Multitask

Table 5: Submitted routes. The open-QA variants are named for their selection criterion.

weaker, and the multitask open-QA route outperforms both specialized alternatives. Task specialization is therefore useful for summarization and development-set context QA, but does not improve open QA in this setting.

Ethics Statement

Public and challenge-provided datasets are used under their respective terms. Machine translation may reproduce source and model biases, and open-ended outputs may contain incorrect or harmful claims. The system should not be treated as a factual authority without verification.

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Task	Official metric	Score	Rank
Context QA	Judge majority	51.70	10/14
Open QA	Judge majority	63.65	7/14
Summarization	Gated ROUGE-L	15.66	4/15

Table 6: Official task results reported on the individual task sheets.

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A Language-Level Changes

Tables 7 and 8 report changes from the multitask adapter on identical held-out examples. All submitted systems share the summary and context routes. The primary system uses Long-form QA, variant A uses Best-score QA, and variant B retains the multitask open-QA route, for which every open-QA change is zero. Context-QA changes are exact-match percentage points; summary and open-QA changes are chrF points. These are descriptive results, and some language cells are small.

Language	n_S	Δ_S	n_C	Δ_C
Arabic	85	+4.39	90	+4.44
Bengali	66	+8.18	20	+10.00
Bhojpuri	14	+26.89	–	–
Czech	14	+12.80	–	–
Central Kurdish	14	+9.23	45	-2.22
German	34	+5.97	93	+3.23
English	70	+0.87	93	+3.23
Finnish	14	+6.59	45	+2.22
French	68	+1.11	45	+0.00
Haitian Creole	34	+1.86	45	+2.22
Hindi	85	+5.40	45	+2.22
Indonesian	85	+3.26	90	+4.44
Italian	34	+3.83	93	+2.15
Japanese	82	+3.02	90	+4.44
Korean	79	+2.03	90	-1.11
Marathi	79	+5.53	45	+0.00
Persian	69	+5.59	45	+6.67
Portuguese	84	+0.09	45	+2.22
Russian	85	+5.10	90	+2.22
Slovak	34	+8.72	45	+2.22
Spanish	85	+4.17	45	+4.44
Swahili	53	+1.88	45	+4.44
Telugu	53	+0.82	45	+0.00
Thai	48	+2.30	45	+2.22
Turkish	84	+2.45	45	+8.89
Vietnamese	84	+4.07	45	+2.22
Yoruba	47	+2.60	–	–
Chinese	68	+1.93	93	+0.00

Table 7: Changes for the shared routes. S denotes summarization (Δ_{chrF}), and C denotes context QA (Δ_{EM} in percentage points).

Language	n	Primary Δ_{chrF}	Var. A Δ_{chrF}
Arabic	52	+0.22	-0.16
Bengali	11	+0.15	-0.72
Czech	11	+1.53	+1.62
German	43	-2.02	-1.34
English	11	-0.18	+1.82
French	45	-1.89	-0.79
Hindi	52	-1.44	+1.75
Indonesian	53	+0.86	+1.50
Italian	45	+2.94	+2.16
Japanese	52	-1.25	-0.84
Korean	45	-0.43	+0.02
Marathi	45	-4.24	-2.62
Portuguese	45	-0.70	-0.68
Russian	52	-1.65	-1.11
Spanish	45	-2.42	-1.57
Turkish	45	+0.21	+1.33
Vietnamese	45	+1.62	+1.00
Yoruba	45	+1.87	+1.57
Chinese	52	+1.38	+0.03

Table 8: Open-QA chrF changes. The primary system uses Long-form QA; variant A uses Best-score QA. Variant B is the multitask reference and has zero change.