An Empirical Study of Many-Shot In-Context Learning for Machine Translation of Low-Resource Languages

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Abstract

In-context learning (ICL) allows large language models (LLMs) to adapt to new tasks from a few examples, making it promising for languages underrepresented in pre-training. Recent work on many-shot ICL suggests that modern LLMs can further benefit from larger ICL examples enabled by their long context windows. However, such gains depend on careful example selection, and the inference cost can be prohibitive for low-resource language communities. In this paper, we present an empirical study of many-shot ICL for machine translation from English into ten truly low-resource languages recently added to FLORES+. We analyze the effects of retrieving more informative examples, using out-of-domain data, and ordering examples by length. Our findings show that many-shot ICL becomes more effective as the number of examples increases. More importantly, we show that BM25-based retrieval substantially improves data efficiency: 50 retrieved examples roughly match 250 many-shot examples, while 250 retrieved examples perform similarly to 1,000 many-shot examples.

1 Introduction

Large Language Models (LLMs) have shown strong performance on many natural language processing (NLP) tasks, including generation tasks such as summarization and machine translation (MT) in multilingual settings (Pu et al., 2023; Zhu et al., 2024; Gemini-Team et al., 2024). However, their performance remains limited for very low-resource and endangered languages.

In-context learning (ICL) (Brown et al., 2020; Dong et al., 2024), which leverages few-shot examples, is one of the most promising emergent abilities of LLMs and has shown strong potential for low-resource languages (LRLs) (Lin et al., 2022; Zhang et al., 2023). However, performance does not necessarily improve as the number of few-shot examples increases, leading many studies to limit the number of shots (e.g., to less than 20) (Zhang et al., 2024; Tanzer et al., 2024; Court and Elsner, 2024). This issue has led to various streams of work focusing on choosing the best few-shot examples, either through similarity between examples, retrieving the most similar to target examples, domain effects, and use of pseudo parallel data (Agrawal et al., 2023; Marashian et al., 2025; Pei et al., 2025). However, most of these studies do not cover LRLs where retrieval is often weaker.

Recently, a new paradigm has emerged that focuses on prompting with large numbers of examples, or "many-shot" prompting (e.g., 1,000 examples) (Agarwal et al., 2024). This approach seems beneficial for LRLs that had limited representation during pretraining, and can make better use of a few thousand examples than fine-tuning, which typically requires more data (Adelani et al., 2022; Vieira et al., 2024). However, despite its promise, the high inference cost makes it challenging for practical use. Exploring more effective many-shot example selection could improve its scalability for low-resource language communities.

In this paper, we investigate the effectiveness of many-shot machine translation (MT) from English into 10 truly LRLs with limited exposure during LLM pretraining. We select these languages carefully based on the recency of the benchmarks, focusing on newly added languages in FLORES+. We further examine how to reduce inference costs by retrieving a smaller set of more effective many-shot examples using simple methods such as BM25. Finally, we study the impact of out-of-domain examples, such as religious texts, on in-domain translation performance for Wikipedia, as well as the effect of example ordering from short to long, inspired by curriculum learning.

Our evaluation on both open-weight and proprietary models, such as `Gemini 2.5 Flash` and `GPT-4.1`, shows the effectiveness of the many-shot approach on these languages, where performance

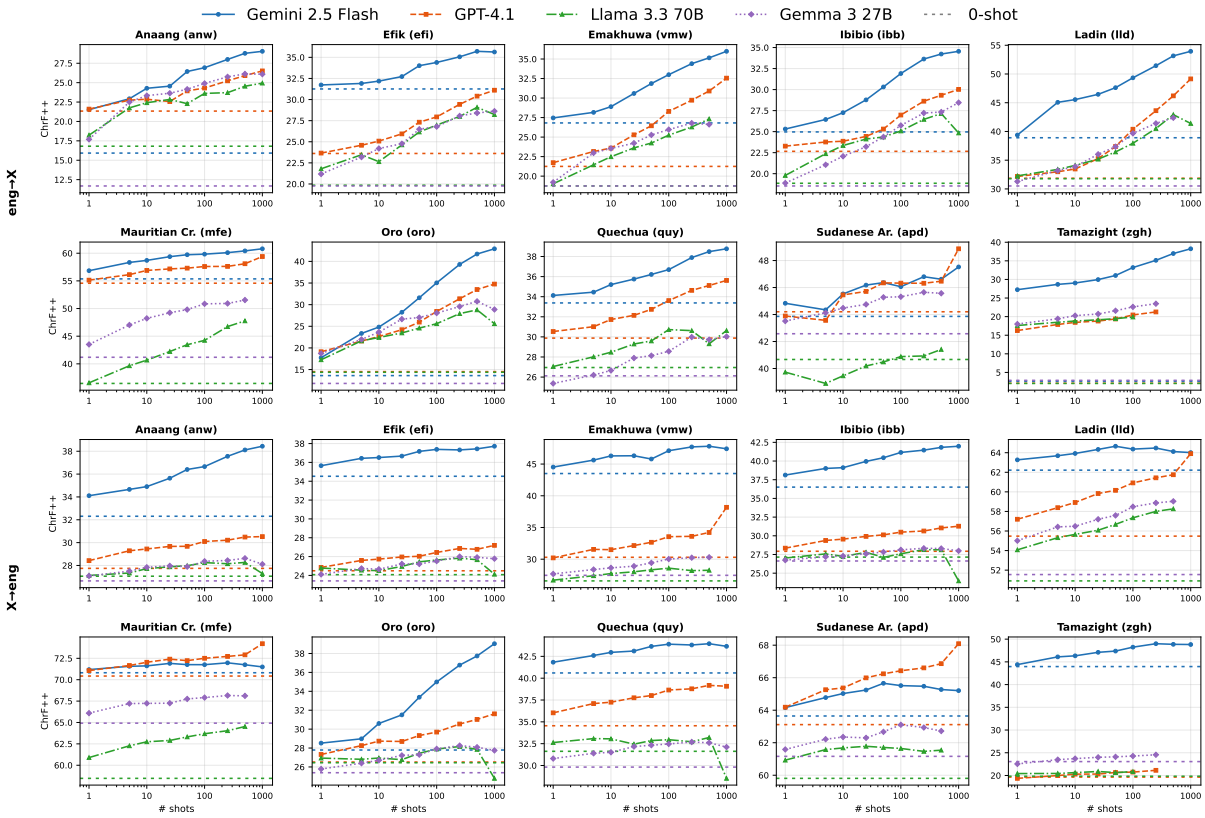

Figure 1: Per-language scaling curves (chrF++, random selection). Top two rows: eng→X; bottom two rows: X→eng.

more than doubles in some languages with more examples. Similarly, leveraging a simple BM25 retrieval from English examples drastically reduces cost, where BM25 with 50 examples roughly matches 250 many-shot examples, and BM25 with 250 examples has similar performance as 1,000 many-shot examples. We find that many shots from within the same domain are consistently better for most languages; however, some languages are not affected by this domain mismatch, which shows some promise in the case of absence of in-domain examples. Finally, the ordering of examples does not seem to have a strong effect on many-shot performance in our experiments.

2 Experimental Setup

2.1 Focus Languages

We focus on ten extremely low-resource languages that were recently added to FLORES+ or extended from FLORES-200 (NLLB Team et al., 2024), including four Nigerian languages (Anaang, Efik, Ibibio, and Oro), Sudanese Arabic, Emakhuwa, Ladin, Mauritian Creole, Tamazight, and Quechua. While Tamazight and Quechua were originally part of FLORES-200, Tamazight has since been improved by the respective community. Eight languages use the Latin script; the exceptions are Tamazight (Tifinagh) and Sudanese Arabic (Arabic script). Appendix A provides more details.

2.2 Experimental Design

For each test sentence, we construct a prompt containing a task instruction, k parallel example pairs (source and target), and the test sentence as a query; the model then generates the translation in one pass. We test $k \in \{0, 1, 5, 10, 25, 50, 100, 250, 500, 1000\}$; the full prompt template appears in Appendix B. We organize the evaluation around three experiments, each targeting one of the research questions.

(1) Scaling We evaluate with randomly sampled examples across several k, and ten languages in two directions ("eng→X" and "X→eng"), using `Gemini 2.5 Flash` (Comanici et al., 2025), `GPT-4.1`, `Llama 3.3 70B` (Grattafiori et al., 2024) and `Gemma 3 27B` (Team et al., 2025).

(2) Example Selection We compare selecting ICL examples randomly vs. BM25 (Robertson

Shots	Method	Anaang	Sudanese	Efik	Ibibio	Ladin	Mauritian	Oro	Quechua	Emakhuwa	Tamazight	Avg
						Gemini 2.5 Flash, eng → X (chrF++)						
5	BM25	**25.8**	**45.7**	**33.5**	**28.7**	**47.6**	**58.6**	**28.6**	**35.9**	**30.9**	**32.0**	36.7
	Random	22.9	44.3	31.9	26.4	45.1	58.3	23.3	34.5	28.2	28.7	34.4
	Δ	+2.9	+1.4	+1.6	+2.3	+2.5	+0.3	+5.3	+1.4	+2.7	+3.3	+2.4
50	BM25	**28.2**	**46.9**	**35.2**	**32.8**	**51.8**	**60.3**	**38.8**	**38.0**	**34.2**	**36.4**	40.3
	Random	26.4	46.4	34.0	30.3	47.6	59.7	31.6	36.2	31.9	31.1	37.5
	Δ	+1.8	+0.5	+1.2	+2.5	+4.2	+0.6	+7.2	+1.8	+2.3	+5.3	+2.7
250	BM25	**28.9**	**46.8**	**35.4**	**34.2**	**53.2**	**60.5**	**41.8**	**38.6**	**35.3**	**37.7**	41.2
	Random	28.0	**46.8**	35.1	33.6	51.4	60.1	39.3	37.9	34.4	35.1	40.2
	Δ	+0.9	0.0	+0.3	+0.6	+1.8	+0.4	+2.5	+0.7	+0.9	+2.6	+1.1
1,000	BM25	**29.5**	47.0	**35.9**	34.4	**54.1**	**61.1**	**43.2**	**38.8**	35.7	**38.3**	41.8
	Random	29.0	**47.5**	35.6	**34.5**	53.9	60.8	42.9	**38.8**	**36.0**	38.2	41.7
	Δ	+0.5	–0.5	+0.3	–0.1	+0.2	+0.3	+0.3	0.0	–0.3	+0.1	+0.1

Table 1: BM25 vs. Rand (chrF++, eng→X, Gemini). **Bold**: winner. Δ: green = BM25 better, red = Random better.

and Zaragoza, 2009) retrieval on the English source side and therefore restrict this experiment to eng→X. We report other advanced retrieval models such as Qwen Embedding model in Appendix D.

(3) Domain Mismatch On the seven languages for which a Bible translation exists (Table 2) [1], we compare Bible-sourced examples against in-domain BM25 and random selection, all in the "eng→X" direction. We retrieve Bible examples with BM25, the same setup as the in-domain experiments, so differences in performance reflect domain rather than retrieval. This tests whether out-of-domain data benefits from scaling the way in-domain data does.

3 Results

Here, we primarily report results using chrF++ (Popović, 2017); results with spBLEU, shown in Appendix C, lead to similar conclusions.

3.1 Effect of Scaling Many-Shot Examples

Figure 1 shows the results for different numbers of ICL examples from $k = 1, 5, .., 1000$. The results show consistent improvement across all LLMs, especially the proprietary models (`Gemini 2.5 Flash` and `GPT-4.1`). In the "eng→X" direction, `Gemini 2.5 Flash` achieves the best overall results across all shot settings, with performance gains ranging from 3.7 to 35.6 from 0-shot to 1,000-shot. Performance is also moderately higher when comparing a few-shot setting, say 10-shot to a many-shot setting, say 1,000-shot, with gains of 2.0 to 18.1. This shows that many-shot prompting leads to larger performance improvements, likely benefiting from the long context windows of modern LLMs. Tamazight benefited the most from few-shot (1-shot) because of its under-represented script, while Oro benefited the most from many-shot. In contrast, the "X→eng" direction shows significantly less improvement than generation into a LRL. However, the trend remains consistently positive except for Sudanese Arabic and Mauritian Creole, which may reflect confusion with related dominant languages such as Arabic and French.

Open weight models experience in-consistencies in higher many-shot `Gemma 3 27B` and `Llama 3.3 70B` sometimes fail at $k = 500$ or $k = 1,000$ due to their limited context window size, and weaker ability to process large numbers of ICL examples. Many-shot is still most effective for proprietary models, aligning with the competence of the base LLM.

Larger many-shot does not always lead to the best performance In some cases, $k = 250$ or $k = 500$ leads to better results than $k = 1,000$, especially in the "X→eng" direction, while for some other languages the performance keeps increasing.

3.2 Example Selection: BM25 vs. Random

Table 1 compares random sampling of ICL examples to BM25 retrieval on the English source side (eng→X).[2] BM25 outperforms random selection for nearly all languages, especially at low shot counts, although the difference narrows as more examples are added. Most importantly, it is more data efficient: 50-shot with BM25 achieves the same average performance as 250-shot of Random ICL (≈ 40.2), and 250-shot BM25 matches 1,000-shot

[1] We excluded Sudanese Arabic Bible based on feedback from native speaker that it is too similar to standard Arabic.

[2] Applied to the English side because applying BM25 to LRLs may yield inconsistent retrieval across languages.

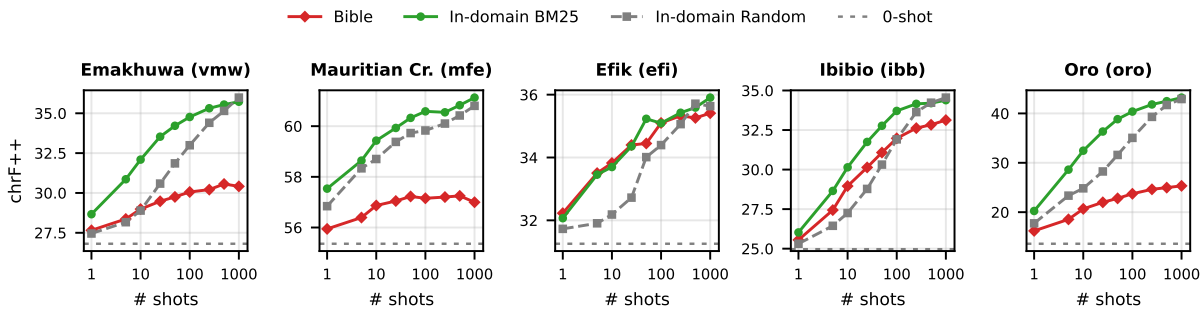

Figure 2: Bible vs. in-domain examples (chrF++, eng→X, Gemini 2.5 Flash). Bible examples plateau or degrade with more shots, while in-domain examples scale consistently.

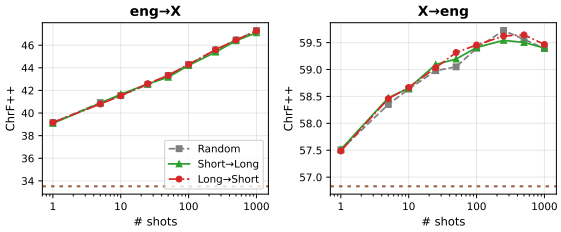

Figure 3: Effect of example ordering on translation quality (chrF++, Gemini 2.5 Flash, averaged across Emakhuwa, Tamazight, Ladin, Mauritian Cr., and Sudanese Ar.). **Short to Long** and **Long to Short** sort examples by source length.

random ICL. This provides more practical usability of many-shot for low-resource communities, drastically reducing inference cost.

3.3 Effect of Out-of-Domain Examples

Figure 2 shows that many-shot ICL from within the same domain (Wikipedia) is more effective than that of out-of-domain (Bible) across all languages. However, some languages do benefit more from the religious domain than others, such as Efik and Ibibio. This finding suggests that all hope is not lost if in-domain examples are not available; out-of-domain examples may still be used, especially if they are similar to the target domain.

3.4 Effect of Ordering ICL Examples

Figure 3 shows the results of ordering examples from Short-to-Long (S2L) and Long-to-Short (L2S). We did not observe any significant impact of ordering the ICL examples by length, especially in the eng→X direction. Semantic relevance through BM25 retrieval seems to be more important.

4 Related Work

While ICL (Brown et al., 2020) has been shown to be very effective on tasks such as machine translation (Dong et al., 2024), performance is highly sensitive to the choice of demonstrations (Luo et al., 2024), including factors such as example order (Lu et al., 2022), diversity (Li and Qiu, 2023), and difficulty (Drozdov et al., 2023). In MT, Agrawal et al. (2023) show that relevance-based retrieval improves few-shot ICL for high-resource languages. However, it remains unclear how example selection interacts with scale in the many-shot setting, particularly for extremely LRLs.

Agarwal et al. (2024) challenge this paradigm by scaling ICL to hundreds or thousands of examples with Gemini 1.5 Pro, showing substantial improvements across summarization, reasoning, and MT, including low-resource translation into Bemba and Kurdish. Salim et al. (2026) investigate scaling in-context token budget to 1M tokens, but the evaluation is limited to smaller models like `Qwen 2.5 7B` with worse performance for larger shots. Our work extends the many-shot setting to a systematic study of 10 extremely LRLs, with a particular focus on retrieval-based example selection and domain effects.

5 Conclusion

In this paper, we study many-shot in-context learning for MT across ten LRLs, scaling from 0 to 1,000 parallel examples and evaluating four LLMs. Performance improves roughly log-linearly as the number of ICL examples increases, with larger gains for translation into LRLs (eng→X) than for X→eng, which shows only moderate improvements. For example selection, retrieval based on similarity on the English side improves sample efficiency: 50 BM25-retrieved examples match the performance of 250 randomly selected ones, and 250 BM25 examples match 1,000 random ICL examples. Out-of-domain ICL examples yield smaller overall gains than in-domain examples, although they remain beneficial for some LRLs.

Limitations

All language pairs in this study involve English as either the source or target language; we did not evaluate non-English-centric translation, which may exhibit different scaling behavior.

Furthermore, we used a single fixed prompt template and did not explore prompt engineering or chain-of-thought strategies, which could affect scaling in ways we have not measured. Additionally, our evaluation is limited to automatic metrics (spBLEU, chrF++); human evaluation would provide a more complete picture of translation quality, particularly for languages where automatic metrics may be less reliable. We also did not explore embedding-based metrics such as COMET (Rei et al., 2020) and MetricX (Juraska et al., 2023) because the languages studied are extremely low-resource and not covered by these metrics.

More broadly, parallel data for extremely low-resource languages may contain annotation errors or inconsistencies, which can affect both the quality of in-context examples and the reliability of reference translations for these automatic evaluation. Hence, translation outputs for these languages should be verified by native speakers before deployment.

Finally, it is important to note that the full set of experiments in this paper required more than $30,000 in API credits, highlighting a significant barrier to reproducibility for low-resource language communities. To mitigate this, we release all results and analyses to reduce the need for others to replicate these costly runs.

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A Languages

We provide the details of the studied languages in Table 2.

ICL examples are sampled from the devtest split (1,012 sentences), and evaluation is performed on the dev split (997 sentences).

For the Bible data, we use versions obtained from bible.com. These texts are used strictly for research purposes without redistribution, in accordance with their terms of use.

B Prompt Templates

All experiments use the following prompt format without any dictionary augmentation.

Many-shot prompt ($k \geq 1$ examples).

```
You are an expert translator. I am going to
give you one or more example pairs of text
snippets where the first is in {SRC} and the
second is a translation of the first snippet
into {TGT}. The sentences will be written
{SRC}: {example_src_1}
{TGT}: {example_tgt_1}
{SRC}: {example_src_2}
{TGT}: {example_tgt_2}
...
{SRC}: {example_src_k}
{TGT}: {example_tgt_k}
After the example pairs, I am going to provide
another sentence in {SRC} and I want you to
translate it into {TGT}. Give only the
translation, and no extra commentary,
formatting, or chattiness. Translate the text
from {SRC} to {TGT}.
{SRC}: {query}
{TGT}:
```

Zero-shot prompt.

```
You are an expert translator. Translate the
text from {SRC} to {TGT}. Give only the
translation, and no extra commentary,
formatting, or chattiness.
{SRC}: {query}
{TGT}:
```

Here `{SRC}` and `{TGT}` are replaced with the full language names (e.g., "English", "Ibibio"). In the many-shot setting, the k example pairs are drawn from the training portion of each dataset, either by random sampling or BM25 retrieval.

C Full Model Results

eng→X. Each table reports Random (in-domain), BM25 retrieval, BM25−Random delta, and Bible (cross-domain) results across all shot counts. Gemini 2.5 Flash: Table 3 (chrF++) and Table 4 (spBLEU). GPT-4.1: Table 5 (chrF++) and Table 6 (spBLEU). Llama 3.3 70B: Table 7 (chrF++) and Table 8 (spBLEU). Gemma 3 27B: Table 9 (chrF++) and Table 10 (spBLEU).

X→eng (random selection only). Table 11 (chrF++) and Table 12 (spBLEU) report X→eng scaling results with random selection across all four models.

Missing entries (–) indicate runs that exceeded the model's context window.

D Ordering Comparison

We test whether the order in which examples appear in the prompt affects translation quality. Table 13 varies the ordering of retrieved examples (BM25 and dense retrieval); Table 14 sorts randomly selected examples by sentence length. In both cases, differences are negligible and no strategy consistently wins.

Language	Family	Morphology	Script	Dataset	Has a Bible?
Emakhuwa (vmw)	Atlantic–Congo / Bantu	Agglutinative	Latin	FLORES+[a]	✓
Moroccan Tamazight (zgh)	Afro-Asiatic / Berber	Fusional	Tifinagh	FLORES+[b]	✗
Ladin (lld)	Indo-European / Romance	Fusional	Latin	FLORES+[c]	✗
Mauritian Creole (mfe)	French Creole	Analytic	Latin	FLORES+[d]	✓
Ay. Quechua (quy)	Quechuan	Agglutinative	Latin	FLORES+[e]	✓
Sudanese Arabic (apd)	Afro-Asiatic / Semitic	Fusional	Arabic	Sudanese-Flores[f]	✓
Anaang (anw)	Atlantic–Congo / Cross River	Agglutinative	Latin	Ibom-NLP[g]	✗
Efik (efi)	Atlantic–Congo / Cross River	Agglutinative	Latin	Ibom-NLP[g]	✓
Ibibio (ibb)	Atlantic–Congo / Cross River	Agglutinative	Latin	Ibom-NLP[g]	✓
Oro (oro)	Atlantic–Congo / Cross River	Agglutinative	Latin	Ibom-NLP[g]	✓

[a] (Ali et al., 2024) [b] (Oktem et al., 2025) [c] (Frontull et al., 2025) [d] (Rajcoomar, 2025)
[e] (NLLB Team et al., 2024) [f] (Samil and Adelani, 2026) [g] (Kalejaiye et al., 2025)

Table 2: Overview of 10 target languages. The bottom four are from the Ibom region of Nigeria.

Table 3: Random, BM25, and Bible examples (eng→X). Gemini 2.5 Flash. chrF++. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	Src	chrF++ (Bible langs)						chrF++ (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	31.3	25.0	55.4	13.6	33.4	26.8	15.9	38.9	2.6	43.9
1	Random	31.7	25.3	56.8	17.7	34.1	27.5	21.5	39.4	27.2	**44.8**
	BM25	**32.1**	**26.0**	**57.5**	**20.2**	**34.5**	**28.7**	**22.7**	**43.8**	**28.6**	44.6
	BM25−Random (△)	+0.3	+0.7	+0.7	+2.5	+0.3	+1.2	+1.2	+4.4	+1.4	−0.2
	Bible	**32.2**	25.6	55.9	16.2	33.6	27.7	✗	✗	✗	✗
5	Random	31.9	26.4	58.3	23.3	34.5	28.2	22.9	45.1	28.7	44.3
	BM25	**33.5**	**28.7**	**58.6**	**28.6**	**35.9**	**30.9**	**25.8**	**47.6**	**32.0**	**45.7**
	BM25−Random (△)	+1.5	+2.2	+0.3	+5.3	+1.5	+2.7	+2.9	+2.5	+3.4	+1.3
	Bible	**33.5**	27.4	56.4	18.5	33.2	28.4	✗	✗	✗	✗
10	Random	32.2	27.3	58.7	24.8	35.2	28.9	24.3	45.5	29.0	45.5
	BM25	**33.7**	**30.1**	**59.4**	**32.5**	**36.7**	**32.1**	**26.7**	**49.1**	**33.8**	**45.7**
	BM25−Random (△)	+1.5	+2.9	+0.7	+7.6	+1.5	+3.2	+2.5	+3.6	+4.7	+0.2
	Bible	**33.8**	29.0	56.9	20.7	32.9	29.0	✗	✗	✗	✗
25	Random	32.7	28.8	59.4	28.2	35.8	30.6	24.6	46.5	30.0	46.2
	BM25	**34.4**	**31.7**	**59.9**	**36.3**	**37.6**	**33.5**	**27.6**	**50.8**	**35.5**	**46.7**
	BM25−Random (△)	+1.6	+3.0	+0.6	+8.1	+1.8	+2.9	+3.1	+4.4	+5.5	+0.5
	Bible	**34.4**	30.1	57.0	22.0	32.7	29.5	✗	✗	✗	✗
50	Random	34.0	30.3	59.7	31.6	36.2	31.9	26.4	47.6	31.1	46.4
	BM25	**35.2**	**32.8**	**60.3**	**38.8**	**38.0**	**34.2**	**28.2**	**51.8**	**36.4**	**46.9**
	BM25−Random (△)	+1.2	+2.5	+0.6	+7.2	+1.8	+2.4	+1.8	+4.1	+5.3	+0.6
	Bible	34.4	31.1	57.2	22.8	32.5	29.8	✗	✗	✗	✗
100	Random	34.4	31.9	59.8	35.0	36.7	33.0	26.9	49.3	33.2	46.1
	BM25	**35.1**	**33.7**	**60.6**	**40.4**	**38.4**	**34.8**	**28.5**	**52.3**	**37.2**	**46.8**
	BM25−Random (△)	+0.7	+1.8	+0.8	+5.3	+1.7	+1.8	+1.6	+3.0	+4.0	+0.8
	Bible	**35.1**	32.0	57.2	23.7	32.6	30.1	✗	✗	✗	✗
250	Random	35.1	33.6	60.1	39.3	37.9	34.4	28.0	51.4	35.1	**46.8**
	BM25	**35.4**	**34.2**	**60.5**	**41.8**	**38.6**	**35.3**	**28.9**	**53.2**	**37.7**	**46.8**
	BM25−Random (△)	+0.4	+0.5	+0.4	+2.5	+0.7	+0.9	+0.9	+1.8	+2.6	0
	Bible	35.3	32.6	57.2	24.6	32.4	30.2	✗	✗	✗	✗
500	Random	**35.7**	**34.2**	60.4	41.7	38.5	35.2	28.8	53.2	37.0	46.6
	BM25	35.6	**34.2**	**60.8**	**42.5**	**38.8**	**35.5**	**29.2**	**53.7**	**38.0**	**47.1**
	BM25−Random (△)	−0.1	0	+0.4	+0.8	+0.3	+0.4	+0.4	+0.5	+1.1	+0.5
	Bible	35.3	32.8	57.2	25.0	32.2	30.6	✗	✗	✗	✗
1000	Random	35.6	**34.5**	60.8	42.9	**38.8**	**36.0**	29.0	53.9	**38.2**	**47.5**
	BM25	**35.9**	34.4	**61.1**	**43.2**	**38.8**	35.7	**29.5**	**54.1**	**38.3**	47.0
	BM25−Random (△)	+0.3	−0.2	+0.3	+0.3	0	−0.3	+0.4	+0.2	0	−0.5
	Bible	35.4	33.1	57.0	25.3	32.5	30.4	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+4.4	+9.6	+5.4	+29.3	+5.4	+9.2	+13.1	+15.0	+35.6	+3.7

Table 4: Random, BM25, and Bible examples (eng→X). Gemini 2.5 Flash. spBLEU. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	**Src**	spBLEU (Bible langs)						spBLEU (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	9.1	6.3	32.2	2.3	9.9	6.4	3.2	17.5	0.8	25.5
1	Random	9.4	6.6	35.5	4.1	10.8	6.8	4.9	18.1	20.0	**26.6**
	BM25	**10.1**	**7.5**	**35.7**	**7.2**	**11.2**	**7.7**	**5.8**	**24.1**	**22.2**	25.9
	BM25−Random (△)	+0.7	+0.9	+0.2	+3.2	+0.4	+0.9	+1.0	+6.0	+2.2	−0.8
	Bible	9.9	7.3	33.7	3.9	10.4	7.0	✗	✗	✗	✗
5	Random	9.6	7.9	37.3	8.8	11.7	7.3	5.3	25.6	22.1	25.2
	BM25	**11.5**	**10.1**	**37.4**	**14.3**	**12.8**	**9.7**	**7.5**	**29.0**	**26.1**	**26.3**
	BM25−Random (△)	+2.0	+2.3	+0.1	+5.5	+1.1	+2.4	+2.2	+3.5	+4.0	+1.1
	Bible	11.4	9.5	34.2	4.8	10.2	7.4	✗	✗	✗	✗
10	Random	9.8	8.2	37.7	9.2	12.1	8.0	6.1	26.1	22.3	26.0
	BM25	**11.9**	**11.5**	**38.3**	**18.1**	**13.5**	**10.7**	**8.0**	**31.1**	**28.0**	**26.3**
	BM25−Random (△)	+2.1	+3.3	+0.6	+8.9	+1.4	+2.7	+2.0	+5.1	+5.7	+0.3
	Bible	11.6	11.0	34.8	5.7	9.7	7.8	✗	✗	✗	✗
25	Random	10.2	9.8	38.5	11.6	12.7	8.9	6.4	27.4	23.6	26.9
	BM25	**12.6**	**13.1**	**39.0**	**22.2**	**14.4**	**12.2**	**8.8**	**33.4**	**29.8**	**27.1**
	BM25−Random (△)	+2.3	+3.3	+0.5	+10.6	+1.7	+3.3	+2.4	+6.1	+6.2	+0.2
	Bible	12.4	12.3	35.1	6.1	9.5	8.2	✗	✗	✗	✗
50	Random	11.2	11.4	39.0	16.2	13.2	10.2	7.6	29.1	24.9	26.9
	BM25	**13.5**	**13.9**	**39.5**	**24.9**	**15.0**	**12.9**	**9.3**	**34.8**	**30.6**	**27.1**
	BM25−Random (△)	+2.3	+2.6	+0.4	+8.7	+1.8	+2.6	+1.7	+5.7	+5.7	+0.2
	Bible	12.4	12.9	35.4	6.5	9.2	8.5	✗	✗	✗	✗
100	Random	11.9	13.0	38.9	19.9	13.6	11.4	8.1	31.4	27.1	26.4
	BM25	**13.4**	**14.7**	**39.9**	**26.7**	**15.3**	**13.4**	**9.5**	**35.6**	**31.2**	**27.0**
	BM25−Random (△)	+1.5	+1.7	+0.9	+6.8	+1.7	+2.0	+1.4	+4.1	+4.2	+0.6
	Bible	13.0	13.9	35.3	6.8	9.4	8.7	✗	✗	✗	✗
250	Random	12.8	14.5	39.3	25.2	14.8	12.8	9.0	34.2	29.2	**27.3**
	BM25	**13.8**	**15.2**	**40.0**	**28.5**	**15.4**	**14.0**	**9.7**	**36.8**	**31.8**	27.1
	BM25−Random (△)	+1.0	+0.7	+0.7	+3.3	+0.6	+1.2	+0.6	+2.6	+2.7	−0.2
	Bible	13.3	14.3	35.4	7.4	9.2	8.9	✗	✗	✗	✗
500	Random	13.6	15.1	39.9	28.1	15.3	13.7	9.7	36.6	30.9	27.2
	BM25	**13.9**	**15.2**	**40.3**	**29.3**	**15.6**	**14.3**	**9.9**	**37.4**	**32.2**	**27.4**
	BM25−Random (△)	+0.3	+0.1	+0.4	+1.3	+0.3	+0.6	+0.2	+0.8	+1.3	+0.2
	Bible	13.1	14.7	35.4	7.7	9.0	9.1	✗	✗	✗	✗
1000	Random	13.5	**15.6**	40.7	30.0	15.6	**14.8**	9.9	37.7	32.2	**28.0**
	BM25	**14.1**	15.4	**40.9**	**30.3**	**15.8**	14.7	**10.2**	**38.0**	**32.6**	27.5
	BM25−Random (△)	+0.6	−0.3	+0.1	+0.4	+0.1	−0.1	+0.3	+0.3	+0.3	−0.5
	Bible	13.2	15.1	35.3	7.9	9.2	9.0	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+4.4	+9.4	+8.5	+27.7	+5.7	+8.4	+6.6	+20.2	+31.4	+2.5

Table 5: Random, BM25, and Bible examples (eng→X). GPT-4.1. chrF++. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	**Src**	chrF++ (Bible langs)						chrF++ (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	23.6	22.7	54.6	14.5	29.9	21.2	21.3	31.9	2.1	44.2
1	Random	23.7	23.3	55.1	19.1	30.5	21.7	21.6	32.2	16.3	**43.9**
	BM25	**24.6**	**24.0**	**55.4**	**21.7**	**30.9**	**23.5**	**22.3**	**33.8**	**18.1**	**43.9**
	BM25−Random (△)	+0.9	+0.7	+0.3	+2.6	+0.4	+1.7	+0.7	+1.6	+1.8	0
	Bible	24.5	23.5	53.8	17.1	30.1	22.1	✗	✗	✗	✗
5	Random	24.6	23.8	56.1	21.6	31.0	23.2	22.7	33.0	17.9	43.6
	BM25	**26.6**	**25.5**	**57.0**	**26.2**	**32.5**	**26.5**	**23.8**	**37.6**	**21.1**	**44.6**
	BM25−Random (△)	+2.0	+1.7	+0.9	+4.6	+1.5	+3.3	+1.0	+4.6	+3.2	+1.0
	Bible	26.5	24.8	53.8	19.5	30.6	23.7	✗	✗	✗	✗
10	Random	25.1	23.9	56.9	22.6	31.7	23.6	22.9	33.5	18.5	**45.5**
	BM25	**27.6**	**26.5**	**57.3**	**28.6**	**33.5**	**27.9**	**24.7**	**39.9**	**22.7**	44.9
	BM25−Random (△)	+2.5	+2.7	+0.4	+5.9	+1.8	+4.3	+1.8	+6.4	+4.3	−0.6
	Bible	27.4	25.5	54.3	20.5	30.8	24.4	✗	✗	✗	✗
25	Random	25.9	24.4	57.2	24.2	32.1	25.3	22.6	35.3	18.8	**45.7**
	BM25	**29.1**	**28.2**	**58.3**	**31.3**	**34.6**	**29.5**	**25.6**	**43.1**	**23.9**	45.4
	BM25−Random (△)	+3.2	+3.7	+1.1	+7.1	+2.4	+4.3	+3.0	+7.8	+5.1	−0.3
	Bible	28.3	26.8	54.0	21.4	30.9	25.7	✗	✗	✗	✗
50	Random	27.3	25.3	57.3	26.0	32.7	26.4	23.9	37.4	19.4	**46.3**
	BM25	**29.9**	**28.9**	**58.5**	**33.0**	**35.2**	**30.7**	**26.1**	**44.8**	**24.2**	45.8
	BM25−Random (△)	+2.6	+3.6	+1.2	+7.1	+2.4	+4.2	+2.2	+7.4	+4.8	−0.5
	Bible	29.2	27.5	54.3	22.0	31.1	26.6	✗	✗	✗	✗
100	Random	27.9	27.0	57.6	28.4	33.6	28.3	24.3	40.4	20.5	**46.3**
	BM25	**30.4**	**29.6**	**58.6**	**34.1**	**35.4**	**31.2**	**26.4**	**46.3**	**24.4**	46.3
	BM25−Random (△)	+2.5	+2.7	+1.0	+5.6	+1.8	+2.9	+2.1	+5.9	+3.9	−0.1
	Bible	29.8	28.3	54.6	22.5	31.2	27.1	✗	✗	✗	✗
250	Random	29.4	28.6	57.6	31.4	34.6	29.7	25.2	43.6	21.3	**46.3**
	BM25	**30.8**	**30.0**	**58.6**	**34.6**	**35.8**	**31.6**	**26.5**	**47.5**	**24.0**	46.2
	BM25−Random (△)	+1.4	+1.4	+0.9	+3.3	+1.1	+1.9	+1.3	+3.9	+2.7	−0.1
	Bible	30.6	29.2	54.7	22.7	31.2	27.8	✗	✗	✗	✗
500	Random	30.4	29.3	58.1	33.5	35.1	30.9	25.9	46.2	–	**46.5**
	BM25	**31.1**	**30.1**	**58.2**	**34.9**	**35.9**	**31.7**	**26.7**	**48.1**	–	46.4
	BM25−Random (△)	+0.7	+0.7	+0.1	+1.4	+0.8	+0.8	+0.8	+1.9	–	−0.1
	Bible	30.8	29.5	54.8	23.3	31.3	28.0	✗	✗	✗	✗
1000	Random	31.1	**30.0**	**59.4**	34.8	35.6	**32.6**	26.5	**49.1**	–	**48.9**
	BM25	**31.4**	**30.0**	58.5	**34.9**	**35.7**	31.9	**26.7**	48.4	–	46.3
	BM25−Random (△)	+0.3	0	−0.9	+0.1	+0.1	−0.7	+0.1	−0.8	–	−2.6
	Bible	30.9	29.7	54.6	23.1	31.4	28.1	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+7.5	+7.4	+4.8	+20.2	+5.7	+11.3	+5.2	+17.3	–	+4.7

Table 6: Random, BM25, and Bible examples (eng→X). GPT-4.1. spBLEU. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	**Src**	spBLEU (Bible langs)						spBLEU (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	6.9	5.8	32.9	2.7	8.0	3.8	5.9	9.8	0.3	25.2
1	Random	6.0	6.6	34.5	5.1	8.1	4.2	5.5	10.3	7.2	**24.8**
	BM25	**6.9**	**7.1**	**34.6**	**8.1**	**8.5**	**5.1**	**5.8**	**12.3**	**10.0**	24.3
	BM25−Random (△)	+0.9	+0.5	+0.1	+3.1	+0.4	+0.9	+0.3	+2.0	+2.8	−0.5
	Bible	**6.9**	6.8	32.3	3.9	7.9	4.4	✗	✗	✗	✗
5	Random	6.4	6.7	35.6	6.8	8.5	4.5	5.9	11.2	9.4	24.3
	BM25	**7.9**	**8.1**	**36.5**	**11.5**	**9.7**	**6.7**	**6.3**	**16.4**	**13.4**	**24.8**
	BM25−Random (△)	+1.5	+1.4	+0.9	+4.7	+1.2	+2.2	+0.4	+5.2	+4.0	+0.4
	Bible	7.7	7.7	32.4	5.0	8.0	4.8	✗	✗	✗	✗
10	Random	6.2	6.5	36.4	7.1	8.9	4.4	5.6	11.6	9.6	**26.1**
	BM25	**8.5**	**8.9**	**36.7**	**13.9**	**10.9**	**7.5**	**6.9**	**19.0**	**15.1**	25.0
	BM25−Random (△)	+2.3	+2.4	+0.4	+6.8	+1.9	+3.1	+1.3	+7.4	+5.5	−1.1
	Bible	8.0	8.2	32.7	5.4	8.2	5.0	✗	✗	✗	✗
25	Random	6.9	6.9	36.6	8.5	9.6	5.1	5.6	13.3	10.0	**26.1**
	BM25	**9.7**	**10.2**	**38.0**	**16.5**	**11.8**	**9.0**	**7.4**	**22.6**	**16.6**	25.5
	BM25−Random (△)	+2.7	+3.3	+1.4	+8.0	+2.2	+3.9	+1.8	+9.3	+6.6	−0.6
	Bible	8.4	9.2	32.1	5.5	8.0	5.6	✗	✗	✗	✗
50	Random	7.6	7.4	36.9	10.4	10.2	6.0	6.1	15.6	10.9	**26.9**
	BM25	**10.2**	**11.0**	**38.2**	**18.5**	**12.5**	**9.8**	**7.9**	**24.7**	**16.9**	26.0
	BM25−Random (△)	+2.6	+3.6	+1.3	+8.1	+2.3	+3.9	+1.8	+9.1	+6.0	−0.9
	Bible	8.8	10.0	32.5	5.8	8.1	6.0	✗	✗	✗	✗
100	Random	8.4	8.7	37.2	12.8	11.0	7.5	6.5	19.2	12.2	**26.6**
	BM25	**10.7**	**11.6**	**38.3**	**19.5**	**12.7**	**10.3**	**8.2**	**26.6**	**17.3**	26.5
	BM25−Random (△)	+2.2	+2.9	+1.1	+6.8	+1.7	+2.8	+1.7	+7.4	+5.1	−0.1
	Bible	9.1	10.5	32.9	5.9	8.1	6.4	✗	✗	✗	✗
250	Random	9.4	10.3	37.2	16.5	11.8	8.8	7.2	23.4	13.3	**26.6**
	BM25	**10.8**	**12.0**	**38.3**	**20.2**	**13.1**	**10.7**	**8.2**	**28.5**	**16.8**	26.4
	BM25−Random (△)	+1.4	+1.6	+1.1	+3.7	+1.3	+2.0	+1.0	+5.1	+3.5	−0.2
	Bible	9.4	11.3	32.8	6.0	7.9	6.7	✗	✗	✗	✗
500	Random	10.4	11.1	37.9	18.9	12.5	10.0	7.7	26.5	–	**26.7**
	BM25	**11.1**	**12.0**	**38.0**	**20.5**	**13.2**	**10.8**	**8.4**	**29.1**	–	**26.7**
	BM25−Random (△)	+0.7	+0.9	+0.1	+1.6	+0.7	+0.7	+0.7	+2.5	–	0
	Bible	9.7	11.4	33.0	6.4	8.0	7.0	✗	✗	✗	✗
1000	Random	11.2	**11.8**	**38.7**	**20.6**	**13.1**	**11.8**	8.3	**30.1**	–	**29.5**
	BM25	**11.4**	**11.8**	38.3	20.5	**13.0**	10.9	**8.4**	29.6	–	26.6
	BM25−Random (△)	+0.2	0	−0.4	−0.1	0	−0.9	+0.2	−0.5	–	−2.9
	Bible	9.8	**11.7**	32.6	6.3	8.0	7.0	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+4.3	+6.0	+5.7	+17.9	+5.1	+8.0	+2.4	+20.3	–	+4.3

Table 7: Random, BM25, and Bible examples (eng→X). Llama 3.3 70B. chrF++. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	Src	chrF++ (Bible langs)						chrF++ (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	19.9	18.9	36.5	14.4	27.0	18.7	16.8	31.8	2.0	40.7
1	Random	21.8	19.8	36.6	17.3	27.1	19.0	18.2	32.3	17.6	39.7
	BM25	**22.8**	**21.6**	**39.3**	**19.8**	**28.1**	**21.2**	**19.8**	**33.7**	**19.6**	**40.2**
	BM25−Random (△)	+1.0	+1.8	+2.7	+2.5	+1.1	+2.2	+1.6	+1.4	+1.9	+0.5
	Bible	22.4	20.1	37.3	16.1	26.9	19.6	✗	✗	✗	✗
5	Random	23.5	22.4	39.7	21.6	28.0	21.5	21.8	33.4	18.5	38.9
	BM25	**25.5**	**24.7**	**43.6**	**26.2**	**30.2**	**24.8**	**23.5**	**37.5**	**21.4**	**40.3**
	BM25−Random (△)	+2.0	+2.3	+4.0	+4.6	+2.1	+3.4	+1.7	+4.1	+3.0	+1.4
	Bible	24.7	22.2	39.6	19.3	27.8	21.7	✗	✗	✗	✗
10	Random	22.6	23.4	40.7	22.4	28.5	22.5	22.4	34.1	18.8	39.5
	BM25	**24.4**	**25.8**	**45.2**	**27.8**	**30.7**	**25.6**	**24.2**	**37.5**	**22.4**	**40.2**
	BM25−Random (△)	+1.7	+2.5	+4.6	+5.3	+2.2	+3.1	+1.8	+3.4	+3.5	+0.7
	Bible	**25.5**	22.0	40.4	20.2	28.2	22.5	✗	✗	✗	✗
25	Random	24.6	24.1	42.2	23.5	29.3	23.6	22.8	35.2	19.1	40.2
	BM25	**26.0**	**26.7**	**47.7**	**29.8**	**30.8**	**27.2**	**24.6**	**39.6**	**22.6**	**40.3**
	BM25−Random (△)	+1.3	+2.6	+5.4	+6.3	+1.5	+3.6	+1.8	+4.4	+3.5	+0.1
	Bible	25.2	24.4	41.3	20.6	28.7	23.3	✗	✗	✗	✗
50	Random	**26.2**	24.4	43.5	24.6	29.6	24.2	22.3	36.4	19.5	40.5
	BM25	25.0	**27.6**	**49.3**	**30.0**	**31.3**	**26.5**	**24.1**	**41.0**	**22.8**	**40.8**
	BM25−Random (△)	−1.1	+3.2	+5.8	+5.5	+1.7	+2.3	+1.8	+4.6	+3.4	+0.3
	Bible	23.6	24.6	41.3	21.0	28.8	23.6	✗	✗	✗	✗
100	Random	**27.0**	25.1	44.2	25.6	30.7	25.2	23.6	37.9	19.9	40.9
	BM25	25.5	**27.3**	**49.8**	**31.1**	**32.0**	**27.6**	**25.1**	**41.5**	**20.2**	**41.3**
	BM25−Random (△)	−1.4	+2.3	+5.5	+5.5	+1.3	+2.4	+1.5	+3.5	+0.3	+0.5
	Bible	**27.7**	23.9	40.7	20.8	28.9	23.6	✗	✗	✗	✗
250	Random	28.0	26.5	46.7	27.9	30.6	26.3	23.7	40.5	–	40.9
	BM25	**28.4**	**27.7**	**50.3**	**30.6**	**32.4**	**27.7**	**24.9**	**42.8**	**10.4**	**41.3**
	BM25−Random (△)	+0.4	+1.3	+3.6	+2.7	+1.8	+1.4	+1.2	+2.3	–	+0.3
	Bible	26.6	24.0	43.7	20.6	28.8	23.3	✗	✗	✗	✗
500	Random	**29.1**	27.2	47.8	28.8	29.3	27.3	24.5	**42.9**	–	41.4
	BM25	27.5	**27.5**	**49.7**	**30.3**	**31.2**	**27.8**	**25.0**	42.7	–	**41.5**
	BM25−Random (△)	−1.6	+0.3	+2.0	+1.5	+1.8	+0.5	+0.4	−0.2	–	+0.1
	Bible	26.8	25.2	40.4	19.8	28.6	22.4	✗	✗	✗	✗
1000	Random	**28.2**	**24.8**	–	**25.6**	**30.6**	–	**24.9**	**41.4**	–	–
	BM25	23.8	20.4	**48.4**	24.9	29.2	**22.9**	23.3	38.4	–	**40.7**
	BM25−Random (△)	−4.4	−4.4	–	−0.7	−1.4	–	−1.6	−3.0	–	–
	Bible	19.2	17.4	38.4	–	–	–	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+8.4	+6.0	–	+11.2	+3.7	–	+8.1	+9.6	–	–

Table 8: Random, BM25, and Bible examples (eng→X). Llama 3.3 70B. spBLEU. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	Src	spBLEU (Bible langs)						spBLEU (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	4.0	4.1	12.9	2.4	6.0	2.5	3.5	9.6	0.3	20.2
1	Random	4.4	3.8	13.0	4.4	6.1	2.5	3.5	10.2	7.2	19.3
	BM25	**5.0**	**5.0**	**15.7**	**6.9**	**6.5**	**3.5**	**4.4**	**12.2**	**10.2**	**19.6**
	BM25−Random (△)	+0.6	+1.2	+2.7	+2.4	+0.4	+1.0	+0.9	+2.0	+3.0	+0.3
	Bible	4.7	4.6	13.8	3.0	5.5	2.7	✗	✗	✗	✗
5	Random	5.1	5.0	15.6	6.3	6.4	3.0	4.3	11.9	8.8	18.1
	BM25	**6.3**	**5.8**	**19.8**	**10.5**	**7.6**	**4.3**	**5.7**	**16.8**	**12.8**	**19.3**
	BM25−Random (△)	+1.2	+0.8	+4.2	+4.2	+1.2	+1.3	+1.4	+4.9	+4.0	+1.2
	Bible	5.6	5.5	15.8	3.7	5.8	3.1	✗	✗	✗	✗
10	Random	**5.3**	5.2	16.4	7.3	6.7	3.4	4.4	12.5	9.9	18.4
	BM25	5.0	**6.3**	**21.6**	**12.1**	**7.9**	**4.9**	**6.2**	**18.0**	**14.3**	**18.7**
	BM25−Random (△)	−0.3	+1.1	+5.2	+4.8	+1.2	+1.4	+1.8	+5.4	+4.5	+0.3
	Bible	**6.1**	5.7	16.7	3.9	5.8	3.3	✗	✗	✗	✗
25	Random	5.6	5.7	18.0	7.4	7.1	3.6	4.9	14.1	10.5	**19.2**
	BM25	**6.3**	**6.9**	**24.0**	**14.1**	**7.6**	**5.8**	**6.6**	**18.2**	**15.1**	19.0
	BM25−Random (△)	+0.7	+1.2	+6.0	+6.7	+0.5	+2.2	+1.7	+4.1	+4.6	−0.3
	Bible	5.9	6.7	17.1	4.2	6.0	3.8	✗	✗	✗	✗
50	Random	**6.2**	5.6	19.5	8.9	7.5	4.3	5.2	15.5	11.0	19.2
	BM25	5.2	**7.8**	**26.5**	**15.0**	**8.7**	**6.1**	**6.5**	**21.6**	**15.9**	**19.5**
	BM25−Random (△)	−1.0	+2.2	+7.0	+6.1	+1.1	+1.7	+1.2	+6.1	+4.9	+0.3
	Bible	5.3	7.1	16.9	4.5	6.3	4.1	✗	✗	✗	✗
100	Random	**7.0**	6.9	20.3	10.4	8.3	5.0	5.8	17.7	11.9	19.5
	BM25	5.5	**8.0**	**26.9**	**16.6**	**9.2**	**6.7**	**7.0**	**21.1**	**14.0**	**20.2**
	BM25−Random (△)	−1.5	+1.1	+6.6	+6.2	+0.8	+1.7	+1.2	+3.4	+2.0	+0.7
	Bible	**7.3**	7.3	18.0	4.6	6.4	4.2	✗	✗	✗	✗
250	Random	**7.9**	8.1	23.2	13.4	9.0	5.7	6.1	20.6	–	19.9
	BM25	7.8	**8.7**	**27.5**	**16.3**	**9.3**	**6.9**	**7.1**	**22.7**	**7.5**	**20.0**
	BM25−Random (△)	−0.1	+0.7	+4.4	+2.9	+0.3	+1.3	+1.1	+2.1	–	+0.1
	Bible	6.8	8.0	20.1	4.8	6.9	4.2	✗	✗	✗	✗
500	Random	**8.7**	8.5	24.6	14.8	**9.2**	6.8	6.5	**23.3**	–	20.2
	BM25	7.1	**8.7**	**27.1**	**16.5**	8.5	**7.3**	**7.1**	22.8	–	**20.4**
	BM25−Random (△)	−1.5	+0.1	+2.5	+1.7	−0.7	+0.5	+0.6	−0.5	–	+0.3
	Bible	7.1	8.0	16.6	4.6	6.7	3.9	✗	✗	✗	✗
1000	Random	**8.7**	**7.6**	–	**13.1**	**9.9**	–	**6.8**	**23.6**	–	–
	BM25	5.9	4.0	**25.4**	12.2	9.3	**5.3**	6.6	21.1	–	**19.8**
	BM25−Random (△)	−2.8	−3.6	–	−1.0	−0.6	–	−0.3	−2.5	–	–
	Bible	4.6	4.4	16.0	–	–	–	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+4.7	+3.5	–	+10.7	+3.9	–	+3.3	+14.0	–	–

Table 9: Random, BM25, and Bible examples (eng→X). Gemma 3 27B. chrF++. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	Src	chrF++ (Bible langs)						chrF++ (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	19.8	18.5	41.2	11.8	26.1	18.7	11.7	30.5	2.9	42.6
1	Random	21.2	18.9	43.5	18.7	25.4	19.2	17.7	31.3	18.0	43.5
	BM25	**22.1**	**20.2**	**45.7**	**19.7**	**26.5**	**21.4**	**19.8**	**33.1**	**19.5**	**43.7**
	BM25−Random (△)	+0.9	+1.3	+2.2	+1.0	+1.1	+2.2	+2.1	+1.8	+1.5	+0.2
	Bible	21.4	18.6	43.0	15.4	25.8	19.7	✗	✗	✗	✗
5	Random	23.2	21.1	47.0	22.0	26.2	23.0	22.5	33.2	19.4	44.1
	BM25	**25.5**	**23.2**	**49.8**	**25.6**	**28.4**	**25.4**	**23.3**	**37.8**	**22.9**	**44.6**
	BM25−Random (△)	+2.3	+2.1	+2.7	+3.7	+2.2	+2.4	+0.8	+4.6	+3.5	+0.4
	Bible	24.1	20.3	44.6	17.9	26.3	22.3	✗	✗	✗	✗
10	Random	24.2	22.1	48.2	23.6	26.7	23.6	23.3	33.9	20.3	44.5
	BM25	**27.0**	**24.7**	**51.8**	**28.2**	**29.2**	**27.1**	**24.1**	**40.3**	**24.8**	**44.7**
	BM25−Random (△)	+2.8	+2.6	+3.6	+4.6	+2.6	+3.6	+0.7	+6.4	+4.5	+0.2
	Bible	25.0	21.7	45.2	18.7	26.6	23.4	✗	✗	✗	✗
25	Random	24.8	23.2	49.2	26.7	27.9	24.2	23.6	36.0	20.7	44.8
	BM25	**28.4**	**26.5**	**53.3**	**31.3**	**30.3**	**28.4**	**25.0**	**43.0**	**26.6**	**45.2**
	BM25−Random (△)	+3.7	+3.3	+4.1	+4.7	+2.4	+4.2	+1.3	+7.0	+5.9	+0.4
	Bible	26.4	22.9	46.0	19.8	26.9	24.2	✗	✗	✗	✗
50	Random	26.5	24.4	49.8	27.0	28.1	25.3	24.2	37.4	21.6	45.3
	BM25	**29.2**	**27.1**	**53.8**	**32.1**	**30.7**	**28.9**	**25.6**	**44.2**	**27.0**	**45.4**
	BM25−Random (△)	+2.7	+2.7	+4.0	+5.1	+2.6	+3.6	+1.5	+6.8	+5.4	+0.2
	Bible	27.0	23.5	46.1	20.1	27.1	24.5	✗	✗	✗	✗
100	Random	26.8	25.7	50.9	28.1	28.6	26.0	24.9	39.7	22.6	45.3
	BM25	**29.5**	**27.6**	**53.7**	**33.1**	**30.7**	**29.0**	**25.9**	**45.2**	**26.9**	**45.8**
	BM25−Random (△)	+2.7	+1.8	+2.8	+5.0	+2.1	+3.0	+1.0	+5.5	+4.3	+0.4
	Bible	27.1	23.9	46.2	19.7	27.4	24.7	✗	✗	✗	✗
250	Random	28.1	27.2	50.9	29.6	30.0	26.8	25.7	41.4	23.5	**45.6**
	BM25	**29.3**	**27.3**	**52.9**	**32.5**	**30.7**	**28.4**	**26.3**	**44.6**	**26.0**	**45.6**
	BM25−Random (△)	+1.3	+0.1	+2.0	+3.0	+0.7	+1.6	+0.5	+3.2	+2.5	0
	Bible	27.4	24.4	46.2	20.0	27.9	24.9	✗	✗	✗	✗
500	Random	28.4	27.3	51.5	30.8	29.7	26.6	**26.1**	42.4	–	45.6
	BM25	**28.9**	**27.6**	**52.0**	**31.4**	**30.5**	**27.5**	26.1	**43.7**	–	**45.7**
	BM25−Random (△)	+0.5	+0.3	+0.5	+0.6	+0.8	+0.9	−0.1	+1.3	–	+0.1
	Bible	26.8	24.1	47.3	20.4	27.7	24.4	✗	✗	✗	✗
1000	Random	28.6	**28.5**	–	**28.9**	**30.0**	–	**26.1**	–	–	–
	BM25	**28.7**	–	–	–	–	–	26.0	–	–	–
	BM25−Random (△)	+0.1	–	–	–	–	–	−0.1	–	–	–
	Bible	26.7	24.2	**45.2**	22.9	27.0	**23.5**	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+8.9	+9.9	–	+17.1	+3.9	–	+14.4	–	–	–

Table 10: Random, BM25, and Bible examples (eng→X). Gemma 3 27B. spBLEU. Per shot: Random in-domain, BM25 retrieval, Δ=BM25−Random, Bible cross-domain. 6 Bible langs; ✗for 4 no-Bible. **Bold**: best per column. Gray: 0-shot. Δ: green=BM25 better, red=Random better. Blue: gain (Random 1000 vs 0-shot).

Shots	Src	spBLEU (Bible langs)						spBLEU (no Bible)			
		efi	ibb	mfe	oro	quy	vmw	anw	lld	zgh	apd
	0-shot	3.6	3.8	17.1	2.5	5.0	3.0	2.0	8.6	0.8	23.5
1	Random	3.8	3.7	19.9	5.1	4.9	3.0	3.7	9.1	9.0	**24.1**
	BM25	**4.8**	**4.9**	**22.2**	**7.4**	**5.5**	**4.1**	**4.8**	**11.8**	**11.7**	**24.1**
	BM25−Random (△)	+0.9	+1.2	+2.4	+2.3	+0.7	+1.0	+1.1	+2.7	+2.8	0
	Bible	4.2	4.1	19.5	3.3	5.2	3.1	✗	✗	✗	✗
5	Random	4.9	5.1	23.1	7.3	5.5	4.4	5.8	11.4	11.3	24.4
	BM25	**6.8**	**6.7**	**26.8**	**11.4**	**7.1**	**5.9**	**6.1**	**17.1**	**15.9**	**24.6**
	BM25−Random (△)	+1.9	+1.7	+3.6	+4.1	+1.6	+1.5	+0.3	+5.7	+4.5	+0.2
	Bible	5.6	5.4	21.2	4.3	5.4	3.5	✗	✗	✗	✗
10	Random	5.3	5.7	24.6	8.5	6.0	4.5	6.1	12.2	12.7	24.6
	BM25	**7.7**	**7.7**	**29.3**	**14.0**	**8.1**	**7.1**	**6.6**	**20.2**	**18.2**	**24.9**
	BM25−Random (△)	+2.4	+2.0	+4.7	+5.5	+2.1	+2.6	+0.6	+8.0	+5.5	+0.2
	Bible	6.0	6.3	21.7	4.6	5.7	3.6	✗	✗	✗	✗
25	Random	6.3	6.4	26.1	10.4	7.1	4.6	6.2	14.5	13.5	24.8
	BM25	**8.9**	**9.1**	**31.5**	**16.6**	**9.1**	**8.5**	**7.0**	**23.6**	**20.5**	**25.0**
	BM25−Random (△)	+2.7	+2.7	+5.4	+6.1	+2.0	+3.9	+0.8	+9.2	+7.0	+0.3
	Bible	7.1	7.2	22.1	5.2	5.7	4.1	✗	✗	✗	✗
50	Random	7.1	7.4	26.9	10.7	7.4	5.9	6.3	16.2	14.8	**25.1**
	BM25	**9.7**	**9.7**	**32.2**	**17.3**	**9.6**	**9.0**	**7.5**	**24.9**	**20.9**	**25.1**
	BM25−Random (△)	+2.6	+2.3	+5.3	+6.6	+2.2	+3.1	+1.1	+8.7	+6.1	0
	Bible	7.6	7.8	22.0	5.4	6.3	4.5	✗	✗	✗	✗
100	Random	7.9	8.3	28.2	11.8	8.0	6.9	6.9	19.2	16.0	25.0
	BM25	**10.3**	**9.7**	**32.0**	**17.7**	**9.7**	**9.3**	**7.9**	**26.1**	**20.9**	**25.4**
	BM25−Random (△)	+2.4	+1.5	+3.9	+5.9	+1.7	+2.4	+1.0	+6.9	+4.8	+0.3
	Bible	7.8	8.2	22.2	5.1	6.3	4.8	✗	✗	✗	✗
250	Random	9.1	9.2	28.6	13.2	9.0	7.6	7.5	21.2	17.0	**25.4**
	BM25	**10.3**	**9.8**	**31.1**	**16.3**	**9.7**	**9.1**	**8.2**	**25.6**	**19.7**	**25.5**
	BM25−Random (△)	+1.3	+0.5	+2.5	+3.1	+0.7	+1.4	+0.7	+4.4	+2.7	0
	Bible	8.2	8.6	22.8	5.8	6.8	5.0	✗	✗	✗	✗
500	Random	9.4	9.5	29.4	13.6	8.7	7.4	8.0	22.5	–	**25.6**
	BM25	**10.1**	**10.1**	**30.0**	**14.6**	**9.5**	**8.4**	**8.1**	**24.4**	–	25.6
	BM25−Random (△)	+0.7	+0.6	+0.6	+1.0	+0.8	+0.9	+0.1	+1.9	–	−0.1
	Bible	7.9	8.2	23.8	6.2	6.5	4.9	✗	✗	✗	✗
1000	Random	**10.3**	**10.4**	–	**12.1**	**9.2**	–	**8.0**	–	–	–
	BM25	9.4	–	–	–	–	–	7.9	–	–	–
	BM25−Random (△)	−0.9	–	–	–	–	–	−0.1	–	–	–
	Bible	7.7	8.4	**22.2**	7.7	6.3	**4.6**	✗	✗	✗	✗
Gain: Random 1000 vs 0-shot		+6.7	+6.6	–	+9.7	+4.2	–	+6.0	–	–	–

Shots	vmw	zgh	lld	mfe	apd	anw	efi	ibb	oro	quy
Gemini 2.5 Flash										
0	43.5	44.0	62.2	70.8	63.6	32.3	34.5	36.5	27.8	40.6
1	44.5	44.4	63.3	71.2	64.2	34.1	35.6	38.1	28.5	41.8
5	45.6	46.1	63.7	71.6	64.8	34.7	36.4	39.0	29.0	42.6
10	46.3	46.3	63.9	71.6	65.0	34.9	36.5	39.1	30.6	43.0
25	46.3	47.1	64.3	71.9	65.2	35.6	36.7	40.0	31.5	43.1
50	45.8	47.4	**64.7**	71.8	**65.7**	36.4	37.2	40.4	33.4	43.6
100	47.1	48.2	64.4	71.8	65.5	36.7	37.4	41.1	35.0	43.9
250	47.7	**49.0**	64.5	**72.0**	65.5	37.6	37.3	41.5	36.8	43.8
500	**47.8**	48.9	64.1	71.7	65.3	38.1	37.4	41.8	37.7	**43.9**
1,000	47.4	48.8	64.0	71.5	65.2	**38.4**	**37.7**	**42.0**	**39.0**	43.7
gain	×1.1	×1.1	×1.0	×1.0	×1.0	×1.2	×1.1	×1.1	×1.4	×1.1
GPT-4.1										
0	30.3	19.6	55.5	70.4	63.1	27.7	24.5	27.9	26.5	34.6
1	30.2	19.4	57.2	71.1	64.2	28.4	24.8	28.3	27.3	36.0
5	31.6	20.0	58.4	71.7	65.3	29.3	25.6	29.4	28.3	37.1
10	31.5	20.3	58.9	72.0	65.4	29.4	25.7	29.6	28.7	37.3
25	32.2	20.3	59.8	72.4	66.0	29.7	26.0	29.9	28.7	37.8
50	32.7	20.7	60.2	72.2	66.2	29.7	26.0	30.1	29.3	38.0
100	33.5	20.7	60.9	72.5	66.4	30.1	26.4	30.5	29.7	38.6
250	33.6	**21.1**	61.4	72.7	66.6	30.2	26.9	30.6	30.5	38.8
500	34.2	–	61.8	72.9	66.9	**30.5**	26.8	31.1	31.0	**39.2**
1,000	**38.2**	–	**63.9**	**74.2**	**68.1**	**30.5**	**27.2**	**31.3**	**31.6**	39.1
gain	×1.3	×1.1	×1.2	×1.1	×1.1	×1.1	×1.1	×1.1	×1.2	×1.1
Llama 3.3 70B										
0	26.6	19.8	50.9	58.5	59.8	27.1	24.1	27.1	26.4	31.6
1	26.7	20.4	54.1	60.9	60.9	27.1	24.8	27.0	26.9	32.6
5	27.4	20.4	55.3	62.3	61.6	27.3	24.6	27.6	26.8	33.1
10	27.7	20.6	55.7	62.7	61.7	27.7	24.5	27.2	26.9	33.1
25	28.0	**20.9**	56.1	62.9	**61.8**	27.9	25.0	27.8	26.8	32.4
50	28.3	20.6	56.7	63.3	61.7	28.0	25.4	27.1	27.4	32.9
100	**28.6**	**20.8**	57.4	63.7	61.6	**28.2**	25.6	27.6	27.9	33.0
250	28.2	–	58.0	64.0	61.5	28.2	**25.8**	**28.1**	**28.2**	32.7
500	28.3	–	**58.3**	**64.5**	61.5	**28.3**	25.7	**28.1**	27.9	**33.2**
1,000	–	–	–	–	–	27.3	24.1	24.0	24.8	28.5
gain	×1.1	×1.1	×1.1	×1.1	×1.0	×1.0	×1.1	×1.0	×1.1	×1.1
Gemma 3 27B										
0	27.5	23.1	51.5	64.9	61.2	26.6	23.4	26.6	25.4	29.8
1	27.7	22.5	55.0	66.1	61.6	27.1	24.1	26.7	25.8	30.8
5	28.4	23.5	56.4	67.2	62.2	27.5	24.7	27.2	26.4	31.4
10	28.6	23.7	56.5	67.2	62.4	27.8	24.7	27.3	26.7	31.5
25	28.9	24.0	57.2	67.3	62.3	28.0	25.2	27.6	27.2	32.2
50	29.4	24.1	57.6	67.8	62.7	27.9	25.2	27.8	27.3	32.3
100	30.0	24.3	58.5	67.9	**63.1**	28.4	25.5	28.1	27.9	32.5
250	30.2	**24.6**	58.9	**68.2**	62.9	28.4	**26.0**	**28.3**	**28.3**	**32.7**
500	**30.3**	–	**59.0**	**68.1**	62.7	**28.6**	25.9	**28.3**	28.1	32.6
1,000	–	–	–	–	–	28.1	25.8	28.0	27.7	32.1
gain	×1.1	×1.1	×1.1	×1.0	×1.0	×1.1	×1.1	×1.1	×1.1	×1.1

Table 11: X→eng scaling with random selection (chrF++). Gray: 0-shot. **Bold**: best per column. *gain*: ratio of best to 0-shot; blue for gain; **green bold** for ≥2×.

Shots	vmw	zgh	lld	mfe	apd	anw	efi	ibb	oro	quy
Gemini 2.5 Flash										
0	23.6	24.3	41.4	54.4	42.4	14.7	17.4	17.4	10.0	20.6
1	24.8	25.0	42.9	54.9	43.1	16.1	18.2	19.5	12.3	22.0
5	26.4	26.8	43.6	55.5	44.8	17.7	18.9	21.4	13.7	23.5
10	27.1	27.0	44.1	55.5	44.7	17.7	19.1	21.4	14.6	23.9
25	27.5	27.8	44.8	**56.0**	45.2	18.6	19.1	22.2	15.3	24.4
50	27.3	28.0	**45.3**	55.8	**45.9**	18.9	19.7	22.6	16.4	25.0
100	28.6	29.1	45.1	55.8	45.7	19.2	19.7	23.1	17.5	25.2
250	28.8	**29.9**	44.9	**56.1**	45.7	19.9	19.6	23.4	19.1	25.0
500	**28.9**	29.3	44.5	55.8	45.7	20.5	19.6	23.9	19.6	**25.4**
1,000	28.5	29.1	44.2	55.5	45.6	**20.5**	**20.1**	**24.0**	**20.7**	24.9
gain	×1.2	×1.2	×1.1	×1.0	×1.1	×1.4	×1.2	×1.4	**×2.1**	×1.2
GPT-4.1										
0	11.7	2.8	33.7	53.3	39.9	11.5	10.4	11.2	8.9	13.8
1	13.2	2.8	36.7	54.7	42.5	12.9	11.0	13.0	11.7	16.8
5	14.6	3.4	38.1	55.4	44.3	13.8	11.3	13.6	12.1	18.4
10	14.8	3.7	39.2	55.9	44.5	14.0	11.6	14.1	12.6	19.1
25	15.4	3.5	40.4	56.6	45.6	14.3	11.7	14.6	12.7	19.9
50	15.7	**3.9**	40.7	56.2	46.0	14.4	11.9	14.6	13.0	20.2
100	16.7	3.6	41.5	56.8	46.4	14.4	12.0	15.1	13.5	21.0
250	16.7	3.7	42.3	57.0	46.6	**14.7**	12.3	15.4	14.1	21.3
500	17.3	–	42.5	57.3	47.0	**14.8**	12.3	**15.7**	**14.3**	**21.6**
1,000	**21.4**	–	**45.6**	**59.3**	**49.4**	14.3	**12.7**	15.4	14.2	21.4
gain	×1.8	×1.4	×1.4	×1.1	×1.2	×1.3	×1.2	×1.4	×1.6	×1.6
Llama 3.3 70B										
0	8.3	1.4	29.1	39.1	36.4	8.9	9.1	9.2	7.6	13.5
1	8.8	2.0	33.3	42.2	38.3	10.3	10.1	10.5	8.9	14.3
5	10.7	2.2	34.7	44.1	39.5	12.0	10.3	11.5	10.4	**15.4**
10	**10.9**	**2.3**	35.3	44.7	40.0	**12.3**	10.5	11.5	10.6	15.4
25	10.4	2.0	35.7	44.6	40.2	11.3	10.5	11.6	9.8	15.3
50	10.5	2.0	36.4	45.2	40.3	11.6	10.9	10.6	10.5	15.2
100	10.8	**2.3**	37.5	45.3	40.2	11.1	10.9	11.8	10.5	14.6
250	10.5	–	38.3	45.4	40.0	11.3	**11.3**	**12.2**	**11.6**	14.0
500	10.5	–	**38.6**	**46.7**	**40.6**	10.6	11.1	11.7	10.3	14.7
1,000	–	–	–	–	–	10.7	10.3	10.5	9.6	13.3
gain	×1.3	×1.6	×1.3	×1.2	×1.1	×1.4	×1.2	×1.3	×1.5	×1.1
Gemma 3 27B										
0	9.2	3.9	30.1	46.6	38.3	9.4	9.6	10.0	6.9	11.0
1	10.5	4.9	34.7	48.1	39.8	10.6	9.9	11.4	8.8	12.6
5	11.5	5.5	36.3	49.7	41.2	11.7	10.6	12.2	10.1	13.9
10	12.0	5.7	36.8	49.7	41.5	**12.1**	10.7	12.1	10.3	14.4
25	12.1	6.0	37.6	49.7	41.9	11.5	10.9	12.3	10.9	15.0
50	12.7	6.0	38.0	50.3	42.5	11.8	11.0	12.6	11.0	15.2
100	13.3	6.4	39.5	50.6	**43.1**	11.8	11.1	12.7	**11.8**	15.6
250	13.3	**6.5**	**39.9**	**50.9**	43.0	11.7	**11.6**	12.7	**11.8**	**15.7**
500	**13.5**	–	39.8	50.8	42.6	11.8	11.4	**12.8**	11.7	**15.6**
1,000	–	–	–	–	–	11.9	11.2	12.7	**11.8**	15.1
gain	×1.5	×1.7	×1.3	×1.1	×1.1	×1.3	×1.2	×1.3	×1.7	×1.4

Table 12: X→eng scaling with random selection (spBLEU). Gray: 0-shot. **Bold**: best per column. *gain*: ratio of best to 0-shot; blue for gain; **green bold** for ≥2×.

Shots	Order	spBLEU					chrF++				
		vmw	zgh	lld	mfe	apd	vmw	zgh	lld	mfe	apd
Gemini 2.5 Flash											
BM25 retrieval											
1	Default	7.7	22.2	24.1	35.7	25.9	28.7	28.6	43.8	57.5	44.6
	Similar first	7.9	22.2	23.8	35.4	25.7	28.8	28.6	43.7	57.3	44.6
	Dissimilar first	7.9	21.8	24.1	35.6	25.8	28.8	28.6	43.8	57.4	44.7
5	Default	9.7	26.1	29.0	37.4	26.3	30.9	32.0	47.6	58.6	45.7
	Similar first	9.7	25.8	29.2	37.6	26.1	30.9	32.1	47.6	58.9	45.5
	Dissimilar first	9.7	25.6	28.9	36.9	26.3	30.9	31.7	47.5	58.5	45.6
10	Default	10.7	28.0	31.1	38.3	26.3	32.1	33.8	49.1	59.4	45.7
	Similar first	10.7	27.5	30.9	38.4	26.5	32.0	33.5	49.0	59.5	46.0
	Dissimilar first	10.8	27.5	30.9	38.0	26.6	32.0	33.4	49.0	59.2	46.1
25	Default	12.2	29.8	33.4	39.0	27.1	33.5	35.5	50.8	59.9	46.7
	Similar first	12.2	29.5	33.3	38.9	27.0	33.4	35.3	50.7	59.8	46.6
	Dissimilar first	12.3	29.5	33.3	38.9	26.9	33.4	35.6	50.7	60.0	46.6
Dense retrieval (Qwen3-Embedding-8B)											
1	Random	7.8	22.0	23.9	35.0	26.0	28.6	28.7	43.8	57.1	44.7
	Similar first	7.7	22.4	24.1	35.1	26.0	28.5	29.0	44.0	57.2	44.6
	Dissimilar first	7.6	21.8	24.1	35.0	26.0	28.6	28.4	43.9	57.0	44.7
5	Random	9.5	24.7	28.0	36.8	26.2	30.8	31.1	46.9	58.5	45.4
	Similar first	9.5	25.0	28.1	37.1	26.2	30.6	31.3	47.0	58.5	45.4
	Dissimilar first	9.5	25.0	27.9	36.9	26.3	30.7	31.1	46.8	58.4	45.4
10	Random	10.5	26.8	29.7	37.6	26.1	31.9	33.0	48.2	58.9	45.6
	Similar first	10.6	26.7	29.9	37.9	26.1	31.8	32.6	48.2	59.2	45.7
	Dissimilar first	10.5	27.1	29.9	37.9	26.4	31.9	32.9	48.2	59.1	45.9
25	Random	11.8	29.0	32.2	38.8	27.2	33.3	34.7	49.8	59.7	46.9
	Similar first	11.9	29.2	32.4	38.0	27.0	33.3	34.9	50.0	59.3	46.5
	Dissimilar first	11.7	28.8	32.7	38.5	27.2	33.1	34.7	50.3	59.7	46.7
GPT-4.1											
BM25 retrieval											
1	Default	5.1	10.0	12.3	34.6	24.3	23.5	18.1	33.8	55.4	43.9
	Similar first	5.3	10.5	12.4	34.6	24.4	23.3	18.2	33.9	55.4	43.9
	Dissimilar first	5.0	10.4	12.4	34.9	24.5	23.4	18.4	34.0	55.7	43.9
5	Default	6.7	13.4	16.4	36.5	24.8	26.5	21.1	37.6	57.0	44.6
	Similar first	6.4	13.6	16.4	36.1	24.7	26.2	21.3	37.6	56.9	44.5
	Dissimilar first	6.5	13.7	16.3	36.0	25.0	26.2	21.3	37.7	56.8	44.8
10	Default	7.5	15.1	19.0	36.7	25.0	27.9	22.7	39.9	57.3	44.9
	Similar first	7.4	15.1	18.9	36.6	25.3	27.6	22.4	39.8	57.3	45.1
	Dissimilar first	7.6	14.9	18.8	36.7	25.3	27.9	22.4	39.8	57.3	45.1
25	Default	9.0	16.6	22.6	38.0	25.5	29.5	23.9	43.1	58.3	45.4
	Similar first	8.7	16.2	22.6	37.6	25.7	29.4	23.6	43.0	58.0	45.6
	Dissimilar first	8.8	16.3	22.7	37.7	25.7	29.5	23.8	43.1	58.1	45.5
Dense retrieval (Qwen3-Embedding-8B)											
1	Random	5.1	9.9	11.6	34.4	24.7	23.4	18.2	33.5	55.4	44.0
	Similar first	5.1	9.6	11.5	34.5	24.7	23.3	18.1	33.4	55.4	44.0
	Dissimilar first	5.0	9.7	11.6	34.5	24.8	23.2	18.1	33.4	55.5	44.1
5	Random	6.3	12.1	14.6	36.1	24.6	25.9	20.4	36.1	56.8	44.5
	Similar first	6.3	12.1	14.6	36.1	24.6	25.8	20.3	36.2	56.9	44.5
	Dissimilar first	6.2	12.2	14.8	35.9	24.8	25.6	20.5	36.3	56.7	44.6
10	Random	7.3	13.2	16.4	36.3	24.9	27.3	21.5	38.0	57.1	44.9
	Similar first	7.1	13.7	16.7	36.5	25.0	27.2	21.8	38.1	57.2	44.9
	Dissimilar first	7.2	13.5	16.6	36.3	24.9	27.3	21.7	38.2	57.1	44.8
25	Random	8.1	14.8	20.4	37.0	25.5	28.9	22.7	41.2	57.7	45.5
	Similar first	8.0	14.7	20.1	36.9	25.5	28.6	22.8	41.0	57.6	45.4
	Dissimilar first	8.2	15.0	20.5	37.0	25.4	28.9	22.7	41.4	57.6	45.4

Table 13: Effect of example ordering within BM25 and dense retrieval (eng→X, FLORES). Left: spBLEU; right: chrF++. For BM25, "Default"=BM25 ranking. for dense, "Random"=shuffle. "Similar/Dissimilar first"=most/least similar closest to query.

Shots	Order	eng→X										X→eng									
		spBLEU					chrF++					spBLEU					chrF++				
		vmw	zgh	lld	mfe	apd	vmw	zgh	lld	mfe	apd	vmw	zgh	lld	mfe	apd	vmw	zgh	lld	mfe	apd
Gemini 2.5 Flash																					
1	Random	6.8	20.0	18.1	35.5	26.6	27.5	27.2	39.4	56.8	44.8	24.8	25.0	42.9	54.9	43.1	44.5	44.4	63.3	71.2	64.2
	L2S	6.9	20.2	18.3	35.3	26.5	27.5	27.4	39.6	56.7	44.7	24.9	24.8	42.9	54.6	43.2	44.6	44.3	63.4	71.0	64.2
	S2L	6.8	19.9	18.3	35.4	26.6	27.3	26.9	39.6	56.7	44.8	24.7	25.1	43.0	54.9	43.1	44.5	44.5	63.4	71.2	64.1
	Pair-L2S	6.8	20.7	18.2	35.5	26.3	27.3	27.7	39.5	56.8	44.6	25.1	25.0	42.7	54.8	43.0	44.7	44.3	63.2	71.1	64.1
	Pair-S2L	6.9	20.2	18.2	35.2	26.2	27.4	27.2	39.5	56.6	44.5	25.0	25.1	42.9	54.7	43.0	44.6	44.4	63.4	71.1	64.0
5	Random	7.3	22.1	25.6	37.3	25.2	28.2	28.7	45.1	58.3	44.3	26.4	26.8	43.6	55.5	44.8	45.6	46.1	63.7	71.6	64.8
	L2S	7.3	21.8	25.3	37.2	25.5	28.0	28.6	44.9	58.1	44.4	26.6	26.9	43.4	55.4	44.6	45.9	46.3	63.7	71.5	64.9
	S2L	7.5	22.3	25.1	36.7	25.6	28.3	28.8	44.7	58.1	44.4	26.8	27.2	43.4	55.6	44.4	45.9	46.3	63.7	71.6	64.9
	Pair-L2S	7.3	21.9	25.5	37.1	26.7	28.0	28.6	45.0	58.3	45.4	26.4	26.9	43.8	55.5	44.6	45.7	46.1	63.8	71.5	64.9
	Pair-S2L	7.5	22.4	25.3	36.9	25.7	28.3	29.0	44.8	58.1	44.9	26.9	27.4	43.9	55.2	44.5	45.8	46.3	64.0	71.4	64.9
10	Random	8.0	22.3	26.1	37.7	26.0	28.9	29.0	45.5	58.7	45.5	27.1	27.0	44.1	55.5	44.7	46.3	46.3	63.9	71.6	65.0
	L2S	8.0	22.5	26.1	37.4	26.6	29.0	29.0	45.4	58.6	45.6	26.8	27.2	44.4	55.8	44.8	45.8	46.6	64.1	71.8	65.0
	S2L	8.3	22.6	26.0	37.8	26.5	29.1	28.9	45.4	59.0	45.8	26.4	27.5	44.1	56.1	44.7	45.9	46.5	63.8	71.9	65.1
	Pair-L2S	7.7	22.3	25.7	37.3	26.9	28.6	28.9	45.1	58.5	46.1	26.8	27.5	44.5	55.9	44.4	46.0	46.7	64.1	71.8	64.8
	Pair-S2L	8.1	22.5	26.2	37.7	26.8	29.2	29.3	45.5	58.7	46.0	26.0	27.2	44.3	55.6	45.1	45.5	46.5	63.9	71.7	65.3
25	Random	8.9	23.6	27.4	38.5	26.9	30.6	30.0	46.5	59.4	46.2	27.5	27.8	44.8	56.0	45.2	46.3	47.1	64.3	71.9	65.2
	L2S	9.1	23.7	27.2	37.9	27.8	30.8	29.9	46.3	59.1	46.9	27.6	27.5	44.5	55.9	45.5	46.8	47.0	64.1	71.8	65.6
	S2L	9.0	23.9	27.2	38.6	27.0	30.7	30.1	46.2	59.4	46.3	27.8	27.8	45.1	55.7	45.8	46.7	47.1	64.3	71.8	65.6
	Pair-L2S	9.3	23.8	27.3	37.8	27.4	30.7	29.8	46.3	59.1	46.4	27.9	27.9	44.8	56.5	45.7	46.9	47.2	64.4	72.2	65.5
	Pair-S2L	8.8	23.9	27.5	38.5	27.5	30.4	30.0	46.4	59.3	46.9	27.7	27.5	44.4	56.1	45.7	46.7	46.8	64.1	71.9	65.4
GPT-4.1																					
1	Random	4.2	7.2	10.3	34.5	24.8	21.7	16.3	32.2	55.1	43.9	13.2	2.8	36.7	54.7	42.5	30.2	19.4	57.2	71.1	64.2
	L2S	4.2	7.8	10.2	34.3	24.9	21.6	16.4	32.1	55.0	44.0	13.1	2.8	36.6	54.6	42.5	30.3	19.4	57.2	71.0	64.2
	S2L	4.4	7.6	10.2	34.2	24.7	21.7	16.9	32.0	54.9	43.8	13.1	2.6	36.4	54.7	42.6	30.3	19.2	56.9	71.1	64.3
	Pair-L2S	4.2	7.8	10.2	34.4	24.8	21.7	16.6	32.0	55.0	43.8	13.0	2.6	36.7	54.8	42.5	30.1	19.3	57.1	71.2	64.3
	Pair-S2L	4.0	8.0	10.1	34.4	24.9	21.6	16.7	32.0	55.1	43.9	13.1	2.5	36.7	54.7	42.5	30.2	19.3	57.2	71.1	64.3
5	Random	4.5	9.4	11.2	35.6	24.3	23.2	17.9	33.0	56.1	43.6	14.6	3.4	38.1	55.4	44.3	31.6	20.0	58.4	71.7	65.3
	L2S	4.3	8.8	11.1	35.4	24.6	22.9	17.7	32.9	56.0	43.9	14.2	3.3	38.1	55.2	43.9	31.5	20.2	58.4	71.5	65.1
	S2L	4.4	9.1	11.0	35.5	24.3	23.1	17.7	32.8	56.0	43.6	14.6	3.2	38.5	55.4	44.1	31.6	19.9	58.7	71.6	65.1
	Pair-L2S	4.5	9.1	10.9	35.6	24.6	23.1	17.7	32.9	56.2	44.0	14.6	3.4	38.1	55.4	44.1	31.7	20.2	58.4	71.6	65.2
	Pair-S2L	4.5	9.3	11.0	35.7	24.5	23.2	17.7	32.9	56.2	43.6	14.5	3.3	38.2	55.3	44.1	31.6	19.9	58.5	71.6	65.1
10	Random	4.4	9.6	11.6	36.4	26.1	23.6	18.5	33.5	56.9	45.5	14.8	3.7	39.2	55.9	44.5	31.5	20.3	58.9	72.0	65.4
	L2S	4.2	9.5	11.6	36.0	26.1	23.3	18.4	33.7	56.8	45.5	14.5	3.7	39.1	55.7	44.8	31.6	20.4	59.0	71.9	65.5
	S2L	4.5	9.8	11.6	35.9	25.8	23.7	18.3	33.6	56.6	45.3	14.7	3.6	39.1	55.7	44.2	31.6	20.2	59.0	71.9	65.2
	Pair-L2S	4.3	9.7	11.8	36.3	25.8	23.6	18.4	33.8	56.9	45.2	14.4	3.6	39.0	55.7	44.6	31.7	20.4	58.9	71.9	65.4
	Pair-S2L	4.6	9.6	11.5	36.5	25.5	23.6	18.3	33.4	56.9	44.8	14.6	3.5	38.8	56.0	44.6	31.5	20.3	58.6	72.1	65.4
25	Random	5.1	10.0	13.3	36.6	26.1	25.3	18.8	35.3	57.2	45.7	15.4	3.5	40.4	56.6	45.6	32.2	20.3	59.8	72.4	66.0
	L2S	4.9	9.9	13.5	36.4	26.1	25.0	18.7	35.7	57.2	46.0	15.0	3.5	39.7	56.2	45.8	32.1	20.4	59.4	72.2	66.0
	S2L	5.1	10.0	13.4	36.3	26.3	25.0	18.7	35.5	57.1	46.0	15.0	3.8	40.2	56.2	45.8	31.8	20.5	59.6	72.3	66.1
	Pair-L2S	5.1	9.9	13.3	36.3	26.3	25.0	18.7	35.6	57.1	46.1	15.2	3.8	39.7	56.1	45.5	32.3	20.6	59.5	72.2	65.9
	Pair-S2L	5.1	9.8	13.3	36.9	26.0	25.1	18.5	35.2	57.5	45.9	15.4	3.8	39.7	55.6	45.7	32.2	20.5	59.3	71.8	66.0

Table 14: Effect of length-based example ordering. Random: no ordering; L2S: Long-to-Short; S2L: Short-to-Long. Pair-L2S/Pair-S2L: ordered by the combined source+target length.