AFRIDOC-MT: Document-level MT Corpus for African Languages

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Abstract

This paper introduces AFRIDOC-MT, a document-level multi-parallel translation dataset covering English and five African languages: Amharic, Hausa, Swahili, Yorùbá, and Zulu. The dataset comprises 334 health and 271 information technology news documents, all human-translated from English to these languages. We conduct document-level translation benchmark experiments by evaluating neural machine translation (NMT) models and large language models (LLMs) for translations between English and these languages, at both the sentence and pseudo-document levels. These outputs are realigned to form complete documents for evaluation. Our results indicate that NLLB-200 achieved the best average performance among the standard NMT models, while GPT-4o outperformed general-purpose LLMs. Fine-tuning selected models led to substantial performance gains, but models trained on sentences struggled to generalize effectively to longer documents. Furthermore, our analysis reveals that some LLMs exhibit issues such as under-generation, repetition of words or phrases, and off-target translations, especially for African languages.

1 Introduction

The field of machine translation (MT) has seen notable progress in the past years, particularly with neural machine translation (NMT) models achieving close to human performance in many high-resource languages (Vaswani et al., 2017; Akhbardeh et al., 2021; Mohammadshahi et al., 2022; Team et al., 2024; Yuan et al., 2023; Kocmi et al., 2023). However, efforts have primarily been concentrated on sentence-level translation, without the use of inter-sentential context.

In recent years, there has been interest in document-level translation (i.e. the holistic translation of multiple sentences), where sentences are translated with their context rather than in isolation. Document-level translation is important in order to capture discourse relations (Bawden et al., 2018; Voita et al., 2018; Maruf et al., 2021), maintain consistency and coherence across sentences (Herold and Ney, 2023), particularly for technical domains, but poses unique challenges, such as how to handle longer documents (Wang et al., 2024b) given the limited context size of translation models. Current efforts have primarily focused on high-resource language directions, where document-level datasets are readily available (Lopes et al., 2020; Feng et al., 2022; Wu et al., 2023; Wang et al., 2023; Wu et al., 2024), and so far there has been no work on low-resource African languages. Developing and evaluating document-level MT systems for low-resource languages is a useful and under-studied direction, which requires the creation of datasets.

To fill this gap, we present AFRIDOC-MT, a document-level translation dataset for English from and into five African languages: Amharic, Hausa, Swahili, Yorùbá, and Zulu, created through the manual translation of English documents. The dataset, drawn from 334 *health* documents and 271 *tech* documents, contains $10,000$ sentences per domain for each language pair. In addition, AFRIDOC-MT supports multi-way translation, allowing translations not only between English and the African languages but also between any two of the languages covered.

We conduct a comprehensive set of document translation benchmark experiments on AFRIDOC-MT, using sentence-level and pseudo-document translation due to most models' limited context length, and then realigning them to form complete documents. We evaluate performance using automatic metrics and compare the results of encoder-decoder models with decoder-only LLMs across both domains. Our results demonstrate that NLLB-200, both before and after fine-tuning on AFRIDOC-MT, excels in sentence translation, surpassing all other models. GPT-4o performs equally

Dataset	#Langs.	Multiway	Domain	Type	#Sents.
TICO-19 (Anastasopoulos et al., 2020)	12	✓	health	document-level	4k
MAFAND-MT (Adelani et al., 2022)	16	✗	news	sentence-level	4k-35k
FLORES-200 (NLLB Team et al., 2022)	42	✓	general	sentence-level	3k
NTREX-128 (Federmann et al., 2022)	24	✓	news	sentence-level	1.9k
AFRIDOC-MT (Ours)	5	✓	tech, health	document-level	10k

Table 1: Overview of highly related works, including for each dataset the number of African languages, the domain, the kind of MT task they can be used for and the range of the sentence numbers for each language direction.

well for sentences and pseudo-documents, while other decoder-only models lag behind. In addition, we use GPT-4o as a proxy for human evaluation to compare documents translated sentence by sentence with those translated as pseudo-documents. The evaluation shows that, on average, pseudo-document translations are more fluent and have fewer errors than sentence-level translations. We conducted additional analyses on the models outputs to better understand their behavior. Our analyses show that LLMs often undergenerate, generate repetitions, and produce off-target translations, especially when translating into African languages.

2 Related Work

MT Datasets for African Languages Several MT datasets exist for African languages, including web-mined datasets such as WikiMatrix (Schwenk et al., 2021a) and CCMatrix (Schwenk et al., 2021b). However, they have been adjudged to be of poor quality for certain low-resource subsets, including African languages (Kreutzer et al., 2022). There are also well curated datasets for African languages including the Bible (McCarthy et al., 2020), JW300 (Agić and Vulić, 2019)[1] and MAFAND-MT (Adelani et al., 2022), which are from religious and news domains.

There exist several MT evaluation benchmark datasets for African languages. They can be categorized into two kinds. First, evaluation datasets specifically designed for translating into or from African languages (Ezeani et al., 2020; Azunre et al., 2021; Adelani et al., 2021, 2022, *inter alia*). Second, benchmark datasets covering many languages, including African languages. For example, TICO-19 (Anastasopoulos et al., 2020), NTREX-128 (Federmann et al., 2022), FLORES-101 (Goyal et al., 2022) and FLORES-200 (Team et al., 2024) are a few such datasets. However, most of these datasets are designed for sentence-level MT, primarily drawn from religious or news domains, although some consist of translated sentences originating from the same document. To the best of our knowledge, only TICO-19, a health domain translation benchmark, has the potential to be used for document-level MT, while it is restricted to topics related to COVID-19. Table 1 gives a comparison of the most related existing benchmarks.

[1]The dataset is no longer available for use.

Document-level Neural Machine Translation Document-level NMT aims to overcome the limitations of sentence-level systems by translating an entire document as a whole. Similar to context-aware NMT, which involves translating segments with additional, localized context, it differs in that it involves in principle translating an entire document holistically. Both document-level and context-aware MT allow for the possibility of improving translation quality for context-dependent phenomena such as coreference resolution (Müller et al., 2018; Bawden et al., 2018; Voita et al., 2018; Herold and Ney, 2023), lexical disambiguation (Rios Gonzales et al., 2017; Martínez Garcia et al., 2019), and lexical cohesion (Wong and Kit, 2012; Garcia et al., 2014, 2017; Bawden et al., 2018; Voita et al., 2019). Various methods have been proposed to extend sentence-level models to capture document-level context (Tiedemann and Scherrer, 2017; Libovický and Helcl, 2017; Bawden et al., 2018; Miculicich et al., 2018; Sun et al., 2022). The emergence of LLMs, such as GPT-3 (Brown et al., 2020), Llama (Dubey et al., 2024) and Gemma (Gemma Team et al., 2024), has transformed NLP, including for MT (Zhu et al., 2024b; Lu et al., 2024). Pre-trained on vast amounts of text, LLMs can effectively manage long-range dependencies, making them in principle well-suited for document-level translation. While these models have shown promising results for high-resource languages (Wu et al., 2023; Wang et al., 2023; Wu et al., 2024), research remains limited for low-resource languages (Ul Haq et al., 2020).

3 AFRIDOC-MT Corpus

Languages and their characteristics We cover five languages from the two most common African

Language	Classification	Spkrs. (M)
Amharic [amh]	Afro-Asiatic/Semitic	57.6
Hausa [hau]	Afro-Asiatic/Chadic	78.5
Swahili [swa]	Niger-Congo/Bantu	71.6
Yorùbá [yor]	Niger-Congo/Volta-Niger	45.9
isiZulu [zul]	Niger-Congo/Bantu	27.8

Table 2: Languages in the AFRIDOC-MT corpus, their classification and number of speakers (in millions).

language families: Afro-Asiatic and Niger-Congo. Three languages belong to the Niger-Congo family: Swahili (North-East Bantu), Yorùbá (Volta-Niger) and isiZulu (Southern Bantu). The other two languages belong to the Afro-Asiatic family: Amharic (Semitic) and Hausa (Chadic). Some details of these languages are given in Table 2. Each of these languages has over 20 million speakers and is spoken in different regions of Sub-Saharan Africa: East (Amharic, Swahili), West (Hausa, Yorùbá), and South (isiZulu). All of them use the Latin script except for Amharic, which uses the Ge'ez script. The Latin-script languages use the Latin alphabet with the omission of some letters and the addition of new ones, and the use of diacritics (e.g., Yorùbá). The languages are tonal, except for Amharic and Swahili. Just like English, all languages follow the subject-verb-object word order. Refer to Adelani (2022) for a comprehensive overview of the characteristics of these languages.

Data Collection and Preprocessing We scraped English articles from the websites of Techpoint Africa[2] and the World Health Organization (WHO)[3,4]. The articles cover different topics of different lengths with an average length of 30 and 37 sentences for *health* and *tech* respectively. While our corpus is initially structured at the article level, we aim to make it suitable for sentence-level translation tasks as well. To achieve this, we segmented the raw articles into sentences using NLTK (Bird et al., 2009). To ensure high segmentation quality, we recruited a linguist and a professional translator to verify the correctness of the segmentation and made corrections as needed. Finally, we selected 10k sentences from the collected texts which resulted in 334 and 271 English articles from the *health* and *tech* domains respectively.

Translation We translated the extracted 10k English sentences to the 5 African languages through 4 expert translators per language.[5] The translators were recruited through a language coordinator who is also a native speaker of the language. The 10k sentences were distributed equally among the translators and the translations were done in-context (i.e. the translators translated on the sentence level but had access to the the whole document). Due to the domain-specific nature of the task, before starting the translation process, we conducted a translation workshop, during which three translation experts shared their experiences in creating terminologies and they also shared existing resources with the translators including a short translation guideline (Appendix A.1).

Quality Checks Quality control was conducted using automated quality estimation, followed by manual inspections by our language coordinators. Due to the volume of translations, we also used automated methods to verify the quality of translations, including language identification to confirm translations were in the target language using Google's DETECTLANG function. We used Quality Estimation (QE), specifically AfriCOMET (Wang et al., 2024a), to assess translation quality. Translations scoring below 0.65 were jointly reviewed by translators and language coordinators (see Appendix A.2).

AFRIDOC-MT data split We created train, development (dev), and test splits for each domain. To prevent data leakage, we first identified documents that shared sentences with the same English translation and assigned these documents to the training set. The dev and test sets are derived from the remaining documents. The dev set comprises documents containing 800 to 1000 sentences, whereas the test set includes documents with 1800 to 2000 sentences. This approach ensures that our evaluation dataset sizes are comparable to other popular benchmark datasets such as FLORES and NTREX. Table 3 shows some data statistics, and we provide more data statistics in Appendix A[6].

4 Benchmark Experiments

Given the AFRIDOC-MT data, we conducted both sentence- and document-level translation, evaluating two types of models: encoder-decoder and decoder-only models. While the majority of these

[2] https://techpoint.africa/
[3] https://www.who.int/health-topics
[4] https://www.who.int/news-room/

[5] Each translator was paid \$1,250 for 2,500 sentences.
[6] We will release AFRIDOC-MT on GitHub under the CC BY-SA 4.0 licence upon acceptance.

Domain	Train	Dev.	Test	Min/Max/Avg
Number of documents				
health	240	33	61	2/151/29.9
tech	187	25	59	8/247/36.9
Number of sentences				
health	7041	977	1982	-
tech	7048	970	1982	-

Table 3: The number of documents and sentences in AFRIDOC-MT, and (at the document level) minimum, maximum and average sentences per document.

models are open-source, we also evaluated two proprietary models of the same type. Our evaluation primarily focuses on document-level translation, reflecting the availability of our document-level translation corpus. For completeness, we also conduct a series of sentence-level experiments, with the results presented in Appendix C.

4.1 Models

Encoder-Decoder Models We evaluate five kinds of open encoder-decoder model including Toucan (Elmadany et al., 2024; Adebara et al., 2024), M2M-100 (Fan et al., 2020), NLLB-200 (Team et al., 2024), MADLAD-400 (Kudugunta et al., 2023), and Aya-101 (Üstün et al., 2024). Toucan is an Africa-centric multilingual MT model that supports 150 African language pairs. In comparison, M2M-100, NLLB-200, and MADLAD-400 are multilingual MT models that cover 100, 200, and 450 language pairs, respectively. Aya-101 is an instruction-tuned mT5 model (Xue et al., 2021), covering 100 languages that is capable of translating between different languages including the African languages considered in AFRIDOC-MT.

Decoder-only Models We also evaluate open and closed decoder-only models. The open models include LLama3.1 (Dubey et al., 2024), Gemma2 (Gemma Team et al., 2024), instruction-tuned versions of LLama3.1 and Gemma2, and LLaMAX3 (Lu et al., 2024), which is a Llama3-based model with continued pre-training on over 100 languages including several African languages, whereas the other models are English-centric. The closed models we test are OpenAI GPT models (GPT-3.5 Turbo and GPT-4o) (OpenAI, 2024), which have been shown to have document-level translation ability (Wang et al., 2023). Although the language coverage of most of these models is not well documented, they demonstrate some understanding of African languages (Adelani et al., 2024b; Bayes et al., 2024), though not at the same level as English, which is the primary language in their training data.

We present the result of 12 models in total, including 1.2B version of Toucan, 1.3B and 3.3B versions of NLLB-200, 3B and 13B versions of MADLAD-400 and Aya-101 respectively. We also have the 8B instruction tuned version of LLama3.1 (LLama3.1-IT), 9B version of Gemma-2 (Gemma2-IT), and LLaMAX3-Alpaca[7]. We provide more description of the models in Appendix B.1.

Supervised finetuning of the models For sentence-level evaluation, we jointly fine-tune NLLB-200 with 1.3B parameters on the 30 language directions and on the two domains to make the models more specialized. Similarly, we did supervised fine-tuning on LLaMAX3 and LLama3.1 using the prompt augmentation approach used by Zhu et al. (2024a) and we describe in Appendix B.4. We chose these two models because LLaMAX3 is already adapted to several languages including our languages of interest, and LLama3.1 because of its long context window. We perform SFT on LLaMAX3 and LLama3.1 for document-level translation, using pseudo-documents with k=10 we refer to them as {model_name}-SFT$_k$[8].

4.2 Experimental Setup

Sentence-level Evaluation Given that our created dataset can be used for sentence-level translation and as a baseline for document-level translation, we evaluate all models on the test splits for each domain. We evaluate the translation models (M2M-100, NLLB-200, and MADLAD-400) using the Fairseq (Ott et al., 2019) codebase for (M2M-100 and NLLB-200), and the Transformers (Wolf et al., 2020) codebase for MADLAD-400. However, for other models including Aya-101, we use the EleutherAI LM Evaluation Harness (`lm-eval`) tool (Biderman et al., 2024) using the three templates listed in Table 19 of Appendix B.4.

Document-level Evaluation Going further, we conduct document-level translation using a similar setup as the sentence-level experiment, but on a few selected models as ideally not all the models have the context length requirement to handle the translation of entire documents. An initial analysis revealed that some models were unable to pro-

[7]we refer to it as LLaMAX3-Alp in the results tables.

[8]we denote models finetuned on sentences as {model_name}-SFT or {model_name}-SFT$_1$

Model	Size	*eng* → *X*						*X* → *eng*						AVG
		amh	hau	swa	yor	zul	Avg.	amh	hau	swa	yor	zul	Avg.	
Encoder-Decoder														
Toucan	1.2B	$33.8_{1.2}$	$57.6_{1.4}$	$70.3_{0.8}$	$36.0_{1.5}$	$58.0_{1.0}$	51.2	$54.7_{1.0}$	$57.7_{1.3}$	$65.2_{0.9}$	$54.0_{1.2}$	$59.9_{0.8}$	58.3	54.7
NLLB-200	1.3B	$49.8_{1.5}$	$64.7_{2.2}$	$75.5_{0.8}$	$45.1_{1.0}$	$69.0_{1.3}$	60.8	$69.4_{1.3}$	$65.3_{1.7}$	$75.3_{0.8}$	$66.3_{1.1}$	$73.2_{0.9}$	69.9	65.4
MADLAD-400	3B	$36.5_{0.9}$	$54.4_{2.0}$	$74.2_{0.9}$	$19.1_{0.9}$	$57.1_{1.4}$	48.3	$68.9_{1.1}$	$63.8_{1.6}$	$76.1_{0.6}$	$51.4_{1.8}$	$68.9_{0.9}$	65.8	57.0
NLLB-200	3.3B	$53.0_{1.9}$	$65.2_{2.2}$	$76.7_{0.7}$	$43.8_{1.1}$	$70.7_{1.3}$	61.9	$70.9_{1.3}$	$66.5_{1.7}$	$77.0_{0.7}$	$67.6_{1.1}$	$74.7_{1.0}$	71.3	66.6
Aya-101	13B	$36.6_{0.9}$	$56.4_{1.5}$	$44.7_{2.4}$	$31.2_{1.4}$	$58.6_{0.8}$	45.5	$64.6_{1.1}$	$61.5_{1.4}$	$70.8_{0.8}$	$57.9_{1.3}$	$67.4_{0.8}$	64.4	55.0
SFT on AfriDoc-MT														
NLLB-SFT	1.3B	$\mathbf{55.9}_{1.6}$	$\mathbf{67.4}_{1.9}$	$\mathbf{81.3}_{0.7}$	$\mathbf{61.5}_{1.0}$	$\mathbf{73.7}_{1.6}$	**68.0**	$\mathbf{72.4}_{1.2}$	$\mathbf{67.5}_{1.6}$	$\mathbf{79.2}_{0.7}$	$\mathbf{71.8}_{1.1}$	$\mathbf{76.5}_{0.9}$	**73.5**	**70.7**
Decoder-only														
Gemma2-IT	9B	$20.1_{0.7}$	$56.4_{1.4}$	$71.2_{0.7}$	$21.0_{0.6}$	$41.6_{1.1}$	42.1	$61.6_{0.9}$	$62.5_{1.3}$	$74.2_{0.7}$	$54.7_{1.3}$	$63.9_{0.9}$	63.4	52.7
LLama3.1-IT	8B	$19.6_{0.5}$	$45.9_{1.4}$	$63.7_{0.9}$	$19.7_{0.6}$	$28.5_{0.7}$	35.5	$53.9_{0.9}$	$59.8_{1.3}$	$69.1_{0.9}$	$53.4_{1.3}$	$54.0_{1.1}$	58.0	46.8
LLaMAX3-Alp	8B	$30.5_{0.8}$	$56.3_{1.5}$	$67.8_{0.8}$	$19.3_{0.8}$	$56.1_{0.9}$	46.0	$63.3_{1.0}$	$62.4_{1.3}$	$71.7_{0.8}$	$56.1_{1.1}$	$65.3_{0.9}$	63.8	54.9
GPT-3.5	–	$20.4_{0.6}$	$44.3_{0.9}$	$76.7_{0.6}$	$21.3_{0.9}$	$51.1_{0.9}$	42.8	$48.3_{0.9}$	$52.4_{1.2}$	$75.0_{0.6}$	$52.1_{1.2}$	$59.5_{0.9}$	57.4	50.1
GPT-4o	–	$36.7_{0.8}$	$64.2_{1.9}$	$79.8_{0.6}$	$29.3_{1.6}$	$69.0_{1.3}$	55.8	$67.2_{1.0}$	$66.5_{1.5}$	$78.1_{0.6}$	$69.1_{1.1}$	$75.1_{1.0}$	71.2	63.5
SFT on AfriDoc-MT														
LLaMAX3-SFT	8B	$46.8_{1.2}$	$62.5_{1.4}$	$73.1_{0.9}$	$57.5_{1.0}$	$67.5_{1.0}$	61.5	$66.6_{1.2}$	$58.9_{1.6}$	$73.1_{1.1}$	$64.7_{1.5}$	$70.5_{1.0}$	66.8	64.1
LLama3.1-SFT	8B	$45.6_{1.1}$	$61.8_{1.5}$	$71.5_{1.0}$	$57.0_{1.1}$	$66.8_{0.9}$	60.6	$64.3_{1.2}$	$59.5_{1.5}$	$72.1_{0.8}$	$64.8_{1.5}$	$69.0_{1.0}$	65.9	63.2

Table 4: Performance of the models in the Health domain, measured by d-CHRF at the sentence-level, realigned to the document-level. For each model and language, the best result from three prompt variations is reported.

Model	Size	*eng* → *X*						*X* → *eng*						AVG
		amh	hau	swa	yor	zul	Avg.	amh	hau	swa	yor	zul	Avg.	
Encoder-Decoder														
Toucan	1.2B	$32.0_{1.6}$	$59.5_{1.7}$	$66.1_{1.7}$	$37.1_{2.0}$	$58.5_{1.4}$	50.7	$54.0_{1.6}$	$59.9_{1.5}$	$64.1_{1.4}$	$54.3_{1.3}$	$59.6_{1.2}$	58.4	54.5
NLLB-200	1.3B	$49.3_{2.0}$	$65.7_{2.2}$	$72.3_{1.6}$	$43.0_{1.3}$	$70.3_{1.3}$	60.1	$69.5_{1.0}$	$66.8_{1.5}$	$72.0_{1.4}$	$63.0_{1.2}$	$71.5_{1.2}$	68.5	64.3
MADLAD-400	3B	$37.3_{1.3}$	$57.0_{2.8}$	$62.1_{2.9}$	$21.3_{1.0}$	$58.5_{1.8}$	47.3	$68.6_{1.1}$	$66.0_{1.4}$	$72.1_{1.4}$	$53.1_{1.4}$	$67.6_{1.2}$	65.5	56.4
NLLB-200	3.3B	$52.2_{2.4}$	$65.4_{2.3}$	$72.8_{1.5}$	$40.1_{1.8}$	$71.6_{1.3}$	60.4	$70.9_{1.0}$	$67.7_{1.5}$	$73.2_{1.4}$	$63.9_{1.1}$	$72.5_{1.2}$	69.6	65.0
Aya-101	13B	$37.3_{1.1}$	$58.9_{2.3}$	$42.4_{2.6}$	$31.4_{1.4}$	$58.9_{1.5}$	45.8	$65.2_{1.2}$	$64.8_{1.2}$	$69.1_{1.1}$	$58.5_{1.3}$	$67.1_{1.1}$	64.9	55.4
SFT on AfriDoc-MT														
NLLB-SFT	1.3B	$\mathbf{53.4}_{2.4}$	$\mathbf{67.9}_{2.2}$	$\mathbf{76.5}_{1.6}$	$\mathbf{59.5}_{1.3}$	$\mathbf{74.0}_{1.5}$	**66.2**	$\mathbf{72.1}_{1.0}$	$69.0_{1.3}$	$74.1_{1.4}$	$\mathbf{67.5}_{1.1}$	$\mathbf{74.3}_{1.1}$	**71.4**	**68.8**
Decoder-only														
Gemma2-IT	9B	$20.6_{0.6}$	$58.3_{1.5}$	$68.7_{1.6}$	$23.9_{1.3}$	$46.5_{1.8}$	43.6	$61.1_{1.3}$	$65.4_{1.4}$	$71.5_{1.2}$	$56.7_{1.3}$	$63.8_{1.1}$	63.7	53.7
LLama3.1-IT	8B	$19.5_{0.9}$	$47.8_{1.3}$	$63.4_{1.5}$	$20.8_{1.2}$	$30.4_{1.3}$	36.4	$51.0_{1.3}$	$61.0_{1.4}$	$66.0_{1.3}$	$53.5_{1.2}$	$52.4_{1.3}$	56.8	46.6
LLaMAX3-Alp	8B	$30.3_{1.1}$	$58.9_{1.9}$	$64.9_{1.7}$	$22.0_{0.8}$	$58.6_{1.7}$	46.9	$63.4_{1.4}$	$64.9_{1.5}$	$69.1_{1.1}$	$56.5_{1.3}$	$65.7_{1.2}$	63.9	55.4
GPT-3.5	–	$22.6_{0.8}$	$49.2_{1.5}$	$72.6_{1.6}$	$23.0_{1.0}$	$53.6_{1.5}$	44.2	$47.4_{1.5}$	$56.5_{1.3}$	$71.5_{1.4}$	$54.0_{1.3}$	$59.9_{1.1}$	57.9	51.0
GPT-4o	–	$36.9_{1.2}$	$65.2_{2.3}$	$75.3_{1.6}$	$29.4_{1.5}$	$71.1_{1.4}$	55.6	$67.2_{1.0}$	$\mathbf{69.1}_{1.4}$	$\mathbf{74.4}_{1.4}$	$66.4_{1.1}$	$73.4_{1.1}$	70.1	62.8
SFT on AfriDoc-MT														
LLaMAX3-SFT	8B	$42.8_{1.5}$	$62.4_{1.9}$	$67.6_{1.4}$	$55.2_{1.5}$	$66.0_{1.2}$	58.8	$63.0_{1.2}$	$53.5_{1.9}$	$67.5_{1.2}$	$57.3_{1.3}$	$66.8_{1.3}$	61.6	60.2
LLama3.1-SFT	8B	$41.6_{1.7}$	$61.8_{2.0}$	$66.4_{1.3}$	$54.9_{1.4}$	$64.6_{1.6}$	57.9	$62.0_{1.2}$	$58.6_{1.5}$	$67.1_{1.2}$	$61.3_{1.3}$	$65.6_{1.3}$	62.9	60.4

Table 5: Performance of the models in the Tech domain, measured by d-CHRF at the sentence-level, realigned to the document-level. For each model and language, the best result from three prompt variations is reported.

cess entire documents due to their maximum input length being shorter than the token counts for some languages, particularly African languages such as Amharic and Yorùbá. To address this, we adopted a pseudo-document approach, splitting documents into smaller, fixed-size chunks of k sentences that fit within the models' token limits. The final chunk in the document could contain fewer than k sentences. We experimented with different chunk sizes (k = 5, 10, 25), with k=1 serving as the sentence-level setup. Based on our findings, we selected k=10 and used this setup for our experiments unless stated otherwise. Table 10 shows the resulting number of parallel pseudo-documents and the average and 95th percentile token counts per pseudo-document for each language and model tokenizer.

4.3 Evaluation Metrics

The evaluation of document-level translation remains a challenge due to the inability of existing automatic metrics to indicate document-level improvements and identify discourse phenomena (Jiang et al., 2022; Dahan et al., 2024), while embedding-based metrics have not yet been explored in the context of African languages. We computed our document-level metrics by first realigning either sentence-level or pseudo-translation outputs into complete documents. Then, we applied the vanilla BLEU and CHRF metrics to these realigned documents, which we refer to as document BLEU (d-BLEU) (Papineni et al., 2002) and document CHRF (d-CHRF) (Popović, 2015). The metrics are calculated using SacreBLEU[9] (Post, 2018) with significance tests based on bootstrap resampling, reporting the 95% confidence intervals for the scores from a sample size of 1000. We report the d-CHRF scores for the best prompt for each model and language direction in the main text, with all additional results provided in the Appendix C.

Furthermore, we use GPT-4o as a proxy for human evaluation to evaluate the translation outputs. Recent works have demonstrated that LLMs can effectively assess translation quality and provide anal-

[9] `case:mixed|eff:no| tok:13a|smooth:exp|v:2.3.1,`

Model	Size	*eng* → *X*						*X* → *eng*						AVG
		amh	hau	swa	yor	zul	Avg.	amh	hau	swa	yor	zul	Avg.	
Encoder-Decoder														
MADLAD-400	3B	$27.5_{1.8}$	$40.2_{2.3}$	$46.6_{3.4}$	$15.1_{0.8}$	$43.6_{2.6}$	34.6	$63.3_{1.6}$	$62.5_{2.0}$	$74.4_{0.9}$	$44.2_{1.6}$	$66.6_{1.5}$	62.2	48.4
Aya-101	13B	$28.7_{1.6}$	$48.5_{2.3}$	$34.7_{3.4}$	$18.7_{1.3}$	$54.9_{1.4}$	37.1	$61.6_{1.7}$	$62.3_{1.8}$	$71.2_{0.9}$	$56.1_{2.1}$	$69.0_{1.0}$	64.0	50.6
Decoder-only														
Gemma2-IT	9B	$6.5_{0.6}$	$37.0_{3.4}$	$52.9_{3.6}$	$6.4_{0.5}$	$12.0_{1.0}$	23.0	$36.5_{3.0}$	$51.8_{3.4}$	$65.0_{3.0}$	$44.8_{2.9}$	$56.1_{3.3}$	50.8	36.9
LLama3.1-IT	8B	$7.5_{0.5}$	$14.0_{1.2}$	$43.2_{3.9}$	$6.4_{0.7}$	$8.7_{0.6}$	16.0	$23.8_{2.3}$	$49.3_{4.1}$	$62.8_{3.3}$	$31.7_{3.9}$	$34.0_{3.7}$	40.3	28.1
LLaMAX3-Alp	8B	$11.4_{0.9}$	$28.9_{2.9}$	$40.4_{3.2}$	$9.2_{0.8}$	$23.6_{1.8}$	22.7	$29.2_{2.1}$	$41.7_{3.8}$	$55.4_{4.9}$	$23.5_{3.0}$	$40.5_{4.7}$	38.1	30.4
GPT-3.5	–	$11.6_{0.5}$	$23.1_{2.0}$	$76.1_{0.6}$	$10.1_{0.9}$	$29.2_{2.1}$	30.0	$41.6_{2.3}$	$52.7_{1.5}$	$77.7_{0.6}$	$51.7_{1.6}$	$61.1_{1.1}$	56.9	43.5
GPT-4o	–	$29.6_{1.7}$	$\mathbf{63.8}_{1.9}$	$\mathbf{80.2}_{0.6}$	$29.6_{2.1}$	$\mathbf{69.5}_{1.6}$	**54.5**	$\mathbf{69.5}_{1.1}$	$\mathbf{69.3}_{1.7}$	$\mathbf{81.0}_{0.6}$	$\mathbf{73.8}_{1.0}$	$\mathbf{78.2}_{1.1}$	**74.4**	**64.4**
SFT on AfriDoc-MT														
LLaMAX3-SFT	8B	$24.1_{1.6}$	$29.0_{3.2}$	$42.2_{4.2}$	$33.8_{2.8}$	$33.7_{3.1}$	32.6	$22.6_{1.8}$	$22.9_{2.6}$	$33.1_{4.4}$	$27.2_{3.6}$	$31.5_{6.7}$	27.5	30.0
LLama3.1-SFT	8B	$25.2_{1.8}$	$31.9_{4.0}$	$50.2_{6.4}$	$33.8_{2.8}$	$38.6_{4.1}$	35.9	$24.2_{3.7}$	$24.1_{4.1}$	$33.7_{5.4}$	$30.2_{4.7}$	$29.3_{6.2}$	28.3	32.1
LLaMAX3-SFT$_{10}$	8B	$\mathbf{37.8}_{2.2}$	$51.9_{5.0}$	$74.4_{3.5}$	$\mathbf{52.2}_{3.3}$	$55.0_{5.5}$	54.2	$64.0_{3.4}$	$66.7_{2.8}$	$77.8_{0.7}$	$71.8_{1.0}$	$74.1_{0.9}$	70.9	62.6
LLama3.1-SFT$_{10}$	8B	$27.6_{2.4}$	$49.7_{5.2}$	$64.1_{5.6}$	$50.3_{2.8}$	$47.0_{4.8}$	47.8	$63.8_{1.1}$	$61.7_{3.5}$	$74.4_{3.5}$	$68.9_{3.4}$	$71.4_{1.0}$	68.0	57.9

Table 6: Performance results of various models on the pseudo-documents (k =10) translation task (Health domain), measured using d-CHRF. The best prompt was selected for each language after evaluating three different prompts.

Model	Size	*eng* → *X*						*X* → *eng*						AVG
		amh	hau	swa	yor	zul	Avg.	amh	hau	swa	yor	zul	Avg.	
Encoder-Decoder														
MADLAD-400	3B	$29.5_{2.1}$	$38.3_{4.3}$	$31.7_{4.6}$	$15.1_{1.1}$	$44.1_{3.6}$	31.8	$62.6_{2.0}$	$63.5_{2.2}$	$66.4_{3.2}$	$45.9_{2.4}$	$63.4_{2.2}$	60.3	46.0
Aya-101	13B	$30.1_{1.5}$	$55.0_{3.2}$	$51.7_{3.5}$	$22.3_{1.7}$	$55.0_{1.9}$	42.8	$62.5_{1.4}$	$65.5_{1.3}$	$68.8_{1.8}$	$55.7_{2.4}$	$68.4_{1.0}$	64.2	53.5
Decoder-only														
Gemma2-IT	9B	$6.2_{0.7}$	$42.1_{3.9}$	$51.0_{5.3}$	$6.6_{0.8}$	$15.4_{1.7}$	24.3	$35.9_{4.8}$	$50.1_{4.6}$	$57.7_{3.7}$	$48.2_{3.4}$	$51.7_{3.7}$	48.7	36.5
LLama3.1-IT	8B	$7.4_{0.9}$	$15.3_{1.9}$	$43.3_{4.4}$	$6.2_{1.1}$	$8.8_{0.7}$	16.2	$26.1_{2.0}$	$48.7_{3.4}$	$59.0_{2.7}$	$34.4_{3.2}$	$34.7_{3.1}$	40.6	28.4
LLaMAX3-Alp	8B	$11.4_{1.2}$	$32.5_{4.4}$	$38.1_{4.1}$	$12.0_{1.4}$	$26.1_{2.2}$	24.0	$29.4_{2.9}$	$51.4_{4.3}$	$62.4_{2.5}$	$24.7_{3.6}$	$48.8_{5.3}$	43.3	33.7
GPT-3.5	–	$13.5_{1.1}$	$29.7_{2.5}$	$72.1_{1.6}$	$12.7_{1.2}$	$35.1_{2.9}$	32.6	$38.5_{4.0}$	$56.3_{1.5}$	$73.5_{1.4}$	$53.0_{1.6}$	$61.2_{1.3}$	56.5	44.6
GPT-4o	–	$31.3_{1.9}$	$\mathbf{65.1}_{2.5}$	$\mathbf{75.1}_{1.6}$	$28.1_{1.8}$	$\mathbf{70.7}_{1.5}$	54.0	$\mathbf{68.6}_{1.1}$	$\mathbf{71.6}_{1.4}$	$\mathbf{76.5}_{1.6}$	$\mathbf{70.1}_{1.1}$	$\mathbf{76.5}_{1.1}$	**72.7**	**63.3**
SFT on AfriDoc-MT														
LLaMAX3-SFT	8B	$21.7_{2.0}$	$29.9_{3.2}$	$37.0_{3.4}$	$30.5_{2.7}$	$31.7_{3.5}$	30.2	$24.2_{2.6}$	$27.6_{4.2}$	$32.3_{4.5}$	$28.5_{3.3}$	$29.8_{5.4}$	28.5	29.3
LLama3.1-SFT	8B	$21.0_{2.0}$	$30.8_{3.2}$	$40.0_{4.1}$	$33.4_{3.8}$	$29.3_{3.1}$	30.9	$23.9_{2.5}$	$28.9_{4.3}$	$36.9_{5.8}$	$32.2_{4.3}$	$32.3_{5.2}$	30.8	30.9
LLaMAX3-SFT$_{10}$	8B	$\mathbf{37.7}_{2.1}$	$58.6_{5.1}$	$68.3_{3.9}$	$49.3_{4.1}$	$60.9_{3.9}$	**55.0**	$65.4_{1.4}$	$68.5_{1.3}$	$73.1_{1.2}$	$67.7_{1.2}$	$71.6_{1.2}$	69.3	62.1
LLama3.1-SFT$_{10}$	8B	$23.7_{1.9}$	$47.0_{5.2}$	$58.6_{5.6}$	$\mathbf{49.7}_{3.8}$	$43.8_{4.5}$	44.5	$60.9_{2.7}$	$65.4_{2.5}$	$71.1_{1.2}$	$66.3_{1.2}$	$66.4_{4.0}$	66.0	55.3

Table 7: Performance results of various models on the pseudo-documents (k =10) translation task (Tech domain), measured using d-CHRF. The best prompt was selected for each language after evaluating three different prompts.

yses of translation errors (Wu et al., 2024; Sun et al., 2024). Following a similar approach to (Sun et al., 2024), we use GPT-4o to assess Fluency, Content Errors (CE), and Cohesion Errors—specifically lexical (LE) and grammatical (GE) errors. However, due to cost constraints, we limit this evaluation to a few model outputs. We provide more details in Appendix B.6.

5 Results

5.1 Sentence-level Evaluation

In Tables 4 and 5 we present d-CHRF scores based on the realigned documents, created by merging the translated sentences into their corresponding documents. We highlight our main findings below, and sentence-level evaluation results using sentence-level metrics are reported in Appendix C.

NLLB-200 outperforms all other encoder-decoder models across languages and domains On average the NLLB models obtain scores of 65.4/66.6 and 64.3/65.0 on *health* and *tech* domains respectively, with 3.3B outperforming 1.3B except when translating into Yorùbá. When translating to English, the least performing model across the two domains is Toucan, however, translating to African languages gives better results than MADLAD-400 and Aya-101. Furthermore, translating to African languages is significantly worse compared to translating to English for all the models.

GPT-4o outperforms other decoder-only counterparts GPT-4o on average outperforms other decoder-only LMs, with average d-CHRF scores of 63.5 and 62.8 for health and tech respectively. The next best performing decoder-only model is LLaMAX3-Alpaca, with d-CHRF scores of 54.9 and 55.4. Unlike other open decoder-based LLMs, LLaMAX3-Alpaca was trained on African languages through continued pretraining and adapted via instruction tuning. It outperforms Gemma2-IT by +2.2 in the health domain and +1.7 in the *tech* domain, particularly when translating into African languages. In contrast, GPT-3.5 and Llama3.1-IT are the least performing models.

Fine-tuning models significantly improves translation quality We obtain improved performance after fine-tuning NLLB-1.3B on AfriDoc-MT, and the resulting model outperforms the 3.3B version without fine-tuning. Similarly, the SFT-based LLMs (LLaMAX3 and LLama3.1) become the best performing open LLMs and outperform their base-

Model	Setup	*eng* → *X*					*X* → *eng*				
		d-CHRF↑	**Fluency↑**	**CE↓**	**LE↓**	**GE↓**	**d-CHRF↑**	**Fluency↑**	**CE↓**	**LE↓**	**GE↓**
Aya-101	Sent	$53.3_{7.5}$	$2.3_{0.9}$	$11.4_{3.0}$	$4.5_{0.5}$	$3.4_{0.2}$	$66.6_{4.7}$	$3.0_{0.3}$	$18.2_{1.3}$	$11.4_{1.2}$	$6.0_{1.9}$
	Doc10	$46.0_{10.3}$	$2.6_{0.7}$	$10.3_{3.5}$	$3.3_{0.9}$	$2.5_{0.6}$	$67.5_{4.6}$	$3.4_{0.3}$	$14.6_{0.8}$	$9.3_{0.9}$	$4.3_{0.3}$
GPT-3.5	Sent	$63.9_{18.1}$	$3.2_{2.4}$	$9.3_{8.6}$	$4.5_{4.2}$	$3.3_{3.0}$	$67.2_{11.0}$	$3.1_{0.7}$	$13.9_{2.6}$	$8.2_{1.2}$	$4.7_{0.9}$
	Doc10	$42.8_{29.0}$	$2.4_{2.1}$	$\mathbf{6.9}_{3.5}$	$\mathbf{2.4}_{1.4}$	$2.2_{1.4}$	$63.8_{12.7}$	$4.3_{0.4}$	$9.2_{2.1}$	$4.8_{0.6}$	$2.4_{0.4}$
LLaMAX3-SFT$_1$	Sent	$\mathbf{67.7}_{5.3}$	$3.4_{0.2}$	$11.2_{1.5}$	$4.5_{0.4}$	$3.5_{0.1}$	$67.5_{7.6}$	$3.4_{0.5}$	$11.5_{1.6}$	$6.2_{1.9}$	$2.9_{0.1}$
	Doc10	$35.0_{6.7}$	$2.6_{0.5}$	$8.9_{0.6}$	$2.9_{0.6}$	$2.2_{0.3}$	$29.2_{5.5}$	$3.0_{0.3}$	$\mathbf{8.8}_{0.2}$	$\mathbf{3.2}_{0.2}$	$\mathbf{2.0}_{0.1}$
LLaMAX3-SFT$_{10}$	Doc10	$60.4_{12.2}$	$\mathbf{4.0}_{0.4}$	$12.4_{2.0}$	$2.8_{0.7}$	$\mathbf{2.0}_{0.2}$	$\mathbf{72.9}_{5.7}$	$\mathbf{4.4}_{0.2}$	$9.0_{0.5}$	$5.2_{0.7}$	$2.5_{0.3}$
GPT-4o	Sent	$71.0_{8.0}$	$4.7_{0.2}$	$3.9_{2.2}$	$1.0_{0.5}$	$0.9_{0.5}$	$73.2_{6.0}$	$3.7_{0.4}$	$11.7_{1.8}$	$7.7_{0.8}$	$3.7_{0.9}$
	Doc10	$71.1_{8.3}$	$4.9_{0.1}$	$3.1_{1.6}$	$0.5_{0.2}$	$0.3_{0.3}$	$76.2_{6.1}$	$4.6_{0.2}$	$7.4_{3.2}$	$4.6_{1.6}$	$2.2_{0.8}$

Table 8: GPT-4o evaluation of selected models for document-level evalaution comparing sentence and document level for Health domain and {hau, swa, zul} ⇔ en. GPT-4o result is self-evaluation. Best scores are in bold.

lines (LLaMAX3-Alpaca and LLama3.1-IT) but below GPT-4o. Overall, our fine-tuned NLLB-200 model is the state-of-the-art model, and our fine-tuned LLaMAX3 is competitive to GPT-4o.

5.2 Document-level Evaluation

In Tables 6 and 7 we present d-CHRF scores based on the best prompt per language for the the translation output of the models when evaluated on the realigned documents from pseudo-documents with k =10 sentences per pseudo-document.

Pseudo-document translation is worse than sentence-level translation when translating into African languages Our results from pseudo-document translation show a performance drop across different models compared to sentence-level translation, especially when translating into African languages. However, GPT-4o demonstrates similar and consistent performance in both setups and domains. Additionally, we observe that GPT-3.5 is the next best performing decoder-only LLM, which contrasts with its performance in sentence-level translation. Gemma2-IT outperforms LLaMAX3-Alpaca especially when translating into English, which also differs from the trends observed in the sentence-level setup.

LLMs trained on longer documents are better for long document translation Both LLama models trained via SFT on sentences (LLama3.1-SFT, and LLaMAX3-SFT) show a decline in performance in the pseudo-document setting compared to sentence-level translation. However, the same models trained via SFT on pseudo-documents with k=10 demonstrate significant improvements on pseudo-documents. Interestingly, the LLaMAX3-SFT$_{10}$ performs consistently well, achieving results comparable to its sentence-level counterpart on sentence-level tasks, and also outperforming LLama3.1-SFT$_{10}$, particularly when translating into African languages.

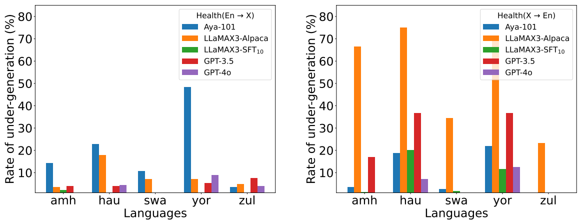

Figure 1: Rate of under-generation in pseudo-document translation (k =10).

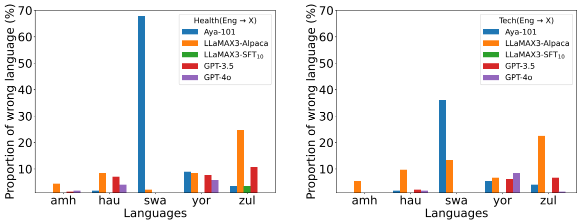

Figure 2: Rate of off-target translation (k =10).

5.3 GPT-4o based evaluation

Table 8 presents the results of the GPT-4o evaluation of realigned documents from both sentence-level tasks and pseudo-document-level tasks (with k=10), focusing on outputs from selected models and translations between English and Zulu/Swahili in the health domain. Our findings indicate that, as anticipated, GPT-4o, when acting as the evaluator, consistently rates its own outputs as the best across all metrics, suggesting potential self-bias. Interestingly, it rates the pseudo-document outputs as more fluent than the sentence-level outputs for both translation directions for all the models. Similarly, the result shows that translating pseudo-documents shows less content errors, lexical error, and grammatical errors. Lastly, LLaMAX3-SFT$_{10}$ has the best evaluation results even incases where d-CHRF does not rate it as best. We discuss this further in Appendix C.3.

6 Discussion and Analysis

In order to better understand the models' behaviour, we analyse their outputs based on frequently observed problems in document-level MT using LLMs (Wu et al., 2024; Wang et al., 2024b).

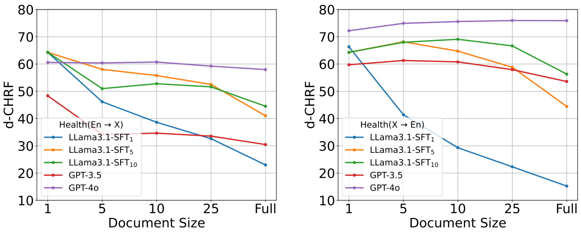

Figure 3: Comparison of Average d-CHRF scores across models and pseudo-document lengths.

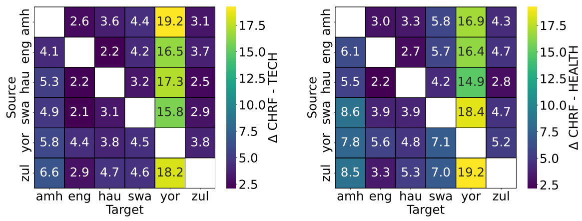

Figure 4: Difference in d-CHRF for NLLB-200 (1.3B) before and after finetuning on AfriDoc-MT for our two domains.

We conduct these analyses on the models' pseudo-document (k =10) translation outputs before merging them into their actual documents, unless stated otherwise. We provide more results in Appendix D.

Are the outputs generated by translation models of appropriate length? We analyzed the translation outputs comparing them to their corresponding reference translation to check wether they are, empty or if the models under-generate. Our analysis shows that all models rarely generate empty translations (refer to Appendix D). However, GPT-3.5 and GPT-4o exhibit a slight tendency to generate empty translations when translating into Yorùbá and Zulu for both domains, though this occurs rarely (less than 10%). For output length, translations with lengths less than 70% of the reference translations were considered under-generated. Figure 1 shows that all the models have the tendency to under-generate. Aya-101 under-generates more than 3% of the pseudo-documents when translating into all the languages from English. LLaMAX3-Alpaca shows at least 10% under-generation across the languages, while other models have less than 30% when translating into English.

Do LLMs generate translations in the correct target languages? We evaluate whether these models understand the task by generating outputs in the target languages using a language identification task. Our results show that these models rarely generate outputs in the wrong language when translating to English. However, when translating to African languages, there is a higher likelihood of incorrect language translations, particularly with open models (Figure 2).

What is the effect of document length on translation quality? We compare the average d-CHRF scores obtained by selected models, including GPT-3.5/4 and LLama3.1-SFT$_k$ where k =1,5,10. The evaluation was conducted across all pseudo-document lengths: 1, 5, 10, 25, and the full length. Figure 3 shows that for translations into African languages, d-CHRF scores decrease as document length increases. A similar trend is observed for the reverse translation, except for GPT-4o, which shows an increasing trend. Also, models trained on long documents generalize better to long documents than those trained on sentences.

What language benefits more from supervised finetuning? We focus on the sentence-level task and translated across all 30 directions for which the model was trained, evaluating both NLLB-200 (1.3B) and its fine-tuned version using d-CHRF. Figure 4 shows performance improvements after supervised fine-tuning of NLLB-200 for both domains. The results shows that translating into Yorùbá, which is the direction with the lowest d-CHRF score from English among all the languages, benefited the most. One major factor contributing to this is the presence of diacritics.

7 Conclusion

In this work, we present AfriDoc-MT, a document-level translation dataset covering two domains *health* and *tech* for 5 African languages. We conducted document-level translation benchmarks, evaluating models of various sizes and fine-tuning selected ones. Due to context length limitations, documents were translated in two ways: (1) sentence by sentence and (2) as pseudo-documents. Outputs were assessed using classical MT metrics and GPT-4o as a proxy for human evaluation. Among built-in MT models, NLLB-200 showed the best performance, while GPT-4o outperformed general-purpose LLMs, with fine-tuning of selected models yielding significant improvements. GPT-4o found pseudo-document translations more fluent and accurate than sentence-level ones, contrasting with classical metrics and highlighting the need for better evaluation metrics. Our analysis also reveals that some LLMs are prone to generating short outputs, off-target translations, and that languages do not benefit equally from fine-tuning.

8 Limitations

Choice of LLMs and Prompts We evaluated only a small subset of the numerous multilingual LLMs available. Our experiments were also limited by the context length of the LLMs, particularly for open LLMs. Except for LLama3.1, all other open LLMs have a context length of 8192 tokens, while encoder-decoder models were primarily based on T5. This makes it difficult to use the context length beyond a certain limit, making full document translation infeasible. Additionally, LLMs are prone to variance in performance based on the prompt; therefore, we evaluated them for translation using three different prompts. However, it is possible that our prompts were not optimal.

Language Coverage Africa is home to thousands of indigenous languages, many of which exhibit unique linguistic properties. However, due to the high cost of translation using human translators and limited available funding, it is currently impossible to cover all languages. As a result, we focused on just five languages. We hope that future work will expand this dataset to include more languages and inspire the creation of additional datasets with broader coverage for document-level translation. Similarly, AFRIDOC-MT is a multi-way parallel dataset. However, due to the cost of running inference over three prompts and across all 30 translation directions for all the models evaluated, most of our analysis is limited to translation tasks between English and the five African languages. While we fine-tuned NLLB-200, LLama3.1 and LLaMAX3 on all 30 directions, we only provide results from NLLB-200 for all directions both before and after fine-tuning for sentence-level and pseudo-document tasks in the Appendix.

Evaluation Metrics Quality evaluation in machine translation is an open and ongoing area of research, especially for document-level translation. Recent works have proposed embedding-based metrics for evaluation at both the sentence and document levels. While this has been well explored for high-resource language pairs, it remains underexplored for African languages, although there is a tool, AfriCOMET, that works for sentence-level evaluation in African languages. Furthermore, we did not carry out human evaluation due to the cost; instead, we used GPT-4 as a proxy. The model's understanding of these languages is not well established, although it achieves comparably the best performance when compared to other decoder-only LLMs. Furthermore, we evaluated a few models and only 3 languages using GPT-4o due to resource constraint.

Ethics Statement

AFRIDOC-MT was created with the utmost consideration for ethical standards. The English texts translated were sourced from publicly available and ethically sourced materials. The data sources were selected to represent different cultural perspectives, with a focus on minimizing any potential bias. Efforts were made to ensure the dataset does not include harmful, biased, or offensive content via manual inspection.

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A More details about AFRIDOC-MT

Table 9 shows the average number of white-space-separated tokens for sentences across various domains and their corresponding translations in all the languages including English. The *health* domain has more tokens on average than *tech*. Hausa and Yorùbá have more tokens on average than English, possibly because they are descriptive languages, while Swahili has a comparably similar length to English. However, Amharic and Zulu have relatively shorter average lengths, demonstrating interesting linguistic properties.

Domain	eng	amh	hau	swa	yor	zul
Sentence						
health	21.6	19.3	28.1	23.2	27.9	16.7
tech	17.8	15.6	22.2	18.0	23.7	13.4
Document						
health	647.3	576.7	841.7	695.4	834.8	500.1
tech	658.2	575.0	821.6	665.4	873.4	495.9

Table 9: The average number of tokens in AFRIDOC-MT, both at sentence and document level.

A.1 Translation Guideline

Below is the translation guideline aside the details shared at the workshop on translation and terminology creation.

- Thank you for agreeing to work on this project. Below is the link to access the data for translation. The files are in .csv format, and you can open them using Google Sheets or Microsoft Excel (for offline work).
- Each file contains 2500 sentences, and they are named in the format of a serial number followed by your first name.
- Please do not delete double empty rows, as they serve to separate paragraphs. Also, avoid deleting any rows, columns, or provided text.
- Use the language field to input the translations. It is essential not to rely on translation engines, as our quality assurance process can detect this. Depending on such tools may result in potential issues that you would need to address, leading to additional work on your part.
- We will provide a list of extracted terminologies soon so that you can harmonize how terminologies are translated.
- Thank you for your attention to these guidelines. Should you have any questions, concerns, or suggestions, feel free to contact us or reach out to your language coordinator.

A.2 Quality evaluation of the translations

As part of the human translation process, we conducted quality estimation to assess the translations. For this purpose, we used AfriCOMET[10]. Given a translated sentence in any African language and its corresponding source English sentence, AfriCOMET generates a score between 0 and 1, where 0 indicates poor quality and higher values signify better quality. The translators, in collaboration with the language coordinators, were

[10] https://huggingface.co/masakhane/africomet-qe-stl

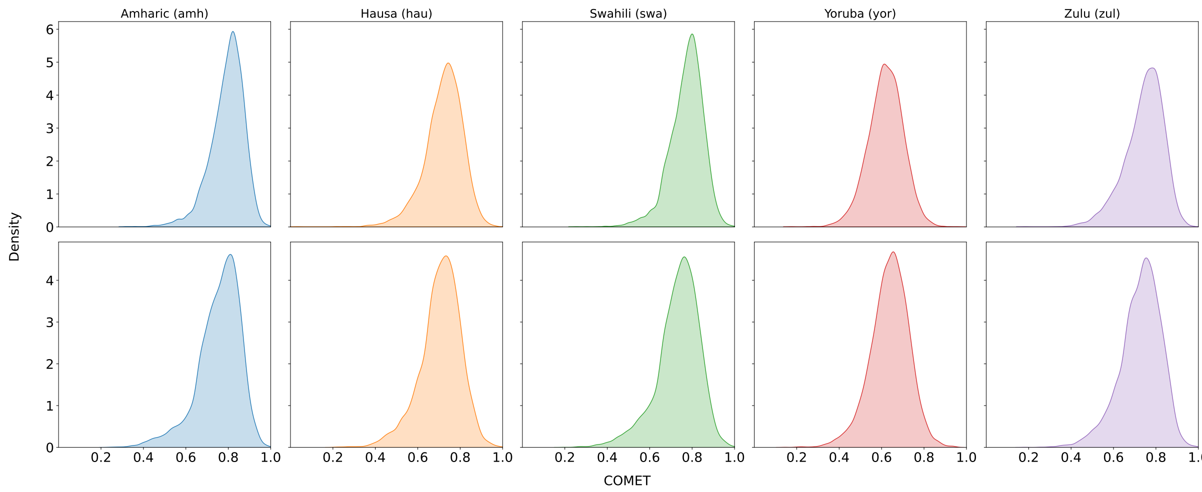

Figure 5: Distribution of the quality estimation of of the translated sentences using COMET scores for the *health* (top), *tech* (bottom).

tasked with reviewing instances that had quality estimation scores below 0.65. This step was essential to identify and correct low-quality translations.

Figure 5 illustrate the distribution of the final quality scores for the five languages and both domains. Our manuel check indicates that QE scores below 0.65 are not necessarily indicative of poor translations, which is consistent with the findings of Adelani et al. (2024b). We attribute this observation to factors such as domain shift, translation length, and other potential influences, which warrant further investigation in future research.

A.3 Creation of Pseudo-documents for AfriDoc-MT

Given that the translated documents vary in length in terms of sentences and tokens, and considering the maximum token length limitations of the different LLMs used, we adopted a chunking approach for document-level evaluation. In this approach, documents were divided into smaller pseudo-documents that fit within the maximum length constraints of the models. To establish an appropriate chunk size, each document was divided into fixed-size chunks of k sentences, with the possibility that the final chunk may contain fewer than k sentences. These sentence groups, referred to as pseudo-documents, were used for document-level translation.

We conducted an initial analysis, testing different values for k (5, 10, and 25), with k=1 serving as our sentence-level setup. Table 10 presents the resulting number of parallel pseudo-documents, as well as the average number of tokens per pseudo-document per language for the various model tokenizers, including the 95th percentile token count. Our analysis revealed that Amharic and Yorùbá —languages with unique characteristics such as non-Latin scripts and diacritics, respectively—had the largest average token counts across the tokenizers. Additionally, domain with highest number of average tokens for pseudo-document vary from language to language.

To accommodate both languages in our experiments, we chose pseudo-documents with k=10. However, for the SFT models described in Section Appendix B.2, we used both k=5 and k=10.

B Experimental details

B.1 Evaluated Models

B.1.1 Translation Models

M2M-100 (Fan et al., 2020) is a transformer-based multilingual neural translation model from Meta, trained to translate between 100 languages, including several African languages. It has three variants of different sizes: 400M parameters, 1.2B parameters, and 12B parameters. For our experiment, we evaluated the 400M and 1.2B variants.

NLLB (Team et al., 2024) is a model similar to M2M-101, with broader coverage, trained to translate between just over 200 languages, including more than 50 African languages. It also has different sizes: 600M, 1.3B, 3.3B, and 54B parameters. However, for this work, we evaluated the first three variants.

Languages/Split	Models	Full		25 sent.		10 sent.		5 sent.	
		Health	Tech	Health	Tech	Health	Tech	Health	Tech
Sizes of data splits in AFRIDOC-MT pseudo-document									
Train		240	187	402	369	812	789	1506	1483
Dev		33	25	56	48	112	106	209	204
Test		61	59	108	106	224	227	417	418
Statistics of LLM tokens in AFRIDOC-MT pseudo-document training splits									
en	NLLB-200	923.7/2017.6	941.9/1982.1	551.5/951.7	477.4/758.8	273.0/430.9	223.2/343.6	147.2/233.8	118.8/184.9
	MADLAD-400	971.0/2095.2	991.4/2100.1	579.7/1017.1	502.4/797.8	287.0/449.3	235.0/362.0	154.7/245.0	125.0/196.9
	Aya-101	1008.2/2183.5	1020.5/2184.3	601.9/1038.0	517.2/820.2	298.0/463.4	241.9/372.6	160.7/255.0	128.7/199.0
	LLaMA3	801.4/1788.0	842.5/1798.4	478.5/833.8	427.0/664.0	236.9/372.9	199.7/304.2	127.8/203.0	106.3/166.0
	Gemma-2	802.9/1820.1	857.9/1857.6	479.3/841.0	434.8/689.6	237.3/375.0	203.4/314.0	128.0/205.0	108.2/169.0
am	NLLB-200	1304.4/2785.8	1376.3/2888.7	778.8/1329.9	697.5/1130.8	385.6/592.0	326.2/520.0	207.9/328.0	173.5/282.9
	MADLAD-400	1624.8/3393.6	1685.0/3487.4	970.0/1684.2	853.9/1380.4	480.2/750.0	399.4/640.2	258.9/413.8	212.5/342.9
	Aya-101	1887.4/3937.9	1934.7/4126.9	1126.8/1931.8	980.5/1598.0	557.9/855.4	458.5/722.0	300.8/477.8	244.0/390.0
	LLaMA3	6798.0/13986.2	6829.6/14750.9	4058.5/6971.8	3461.1/5584.8	2009.3/3084.4	1618.7/2560.8	1083.3/1716.0	861.2/1379.9
	Gemma-2	2817.9/5857.5	2868.4/6227.4	1682.1/2896.4	1453.2/2342.4	832.4/1267.8	679.3/1071.6	448.5/710.0	361.0/575.0
ha	NLLB-200	1204.4/2713.7	1171.4/2463.0	719.0/1252.8	593.6/962.6	356.0/554.0	277.6/430.6	191.9/306.8	147.7/232.0
	MADLAD-400	1297.1/2849.4	1260.5/2643.7	774.4/1359.7	638.8/1042.0	383.4/606.4	298.8/465.6	206.7/329.0	158.9/251.0
	Aya-101	1614.9/3497.4	1535.3/3241.9	964.1/1672.3	778.0/1254.6	477.3/742.6	363.9/563.2	257.4/410.8	193.6/306.0
	LLaMA3	1916.7/4012.9	1822.6/3917.9	1144.3/1988.8	923.7/1513.6	566.6/882.4	432.1/674.6	305.5/488.8	230.0/365.9
	Gemma-2	1642.4/3568.9	1581.3/3373.4	980.6/1716.7	801.4/1297.8	485.5/757.4	374.8/584.0	261.8/417.8	199.4/317.8
sw	NLLB-200	1100.8/2494.8	1094.8/2187.5	657.2/1145.9	554.8/896.4	325.4/517.0	259.5/409.6	175.4/280.0	138.1/218.0
	MADLAD-400	1177.3/2629.9	1155.3/2293.9	702.8/1227.6	585.5/938.6	348.0/547.0	273.8/436.0	187.6/297.0	145.7/231.9
	Aya-101	1345.3/2925.0	1311.0/2667.8	803.2/1390.9	664.4/1076.2	397.6/627.9	310.7/487.4	214.4/339.0	165.3/261.0
	LLaMA3	1668.1/3605.0	1619.4/3364.9	995.9/1735.4	820.7/1330.0	493.1/771.4	383.9/599.8	266.0/418.0	204.3/323.0
	Gemma-2	1413.3/3097.3	1377.1/2770.0	843.8/1467.7	697.9/1126.2	417.8/658.9	326.4/513.0	225.3/356.8	173.7/277.9
yo	NLLB-200	1702.6/3854.7	1724.8/3577.1	1016.5/1857.2	874.1/1428.6	503.2/814.7	408.8/644.6	271.3/443.8	217.5/348.9
	MADLAD-400	1983.6/4470.9	1990.4/4136.7	1184.3/2137.5	1008.7/1650.2	586.3/939.4	471.7/742.2	316.1/512.0	251.0/401.9
	Aya-101	2729.2/5832.3	2659.8/5549.7	1629.4/2956.4	1347.9/2211.6	806.7/1292.4	630.4/988.0	434.9/704.0	335.4/544.0
	LLaMA3	2945.8/6322.4	2880.0/5995.5	1758.6/3203.9	1459.4/2400.4	870.5/1406.0	682.5/1077.6	469.3/767.8	363.0/585.9
	Gemma-2	2620.4/5745.5	2593.5/5406.9	1564.3/2867.7	1314.3/2143.8	774.4/1245.4	614.6/965.6	417.4/678.0	327.0/530.0
zu	NLLB-200	1201.8/2513.3	1230.4/2555.7	717.5/1233.0	623.5/1016.6	355.2/554.3	291.6/461.2	191.5/300.0	155.1/250.0
	MADLAD-400	1215.2/2524.0	1230.7/2519.6	725.5/1284.8	623.7/1007.2	359.2/557.8	291.7/465.6	193.7/305.5	155.2/251.0
	Aya-101	1491.3/3012.2	1485.2/3180.8	890.3/1521.8	752.7/1213.0	440.8/688.9	352.0/554.4	237.7/372.8	187.3/298.9
	LLaMA3	1921.7/3822.6	1834.3/3933.4	1147.3/1963.9	929.7/1512.4	568.1/885.4	434.9/689.2	306.4/475.8	231.5/373.0
	Gemma-2	1787.5/3573.5	1703.0/3666.1	1067.2/1834.8	863.0/1416.2	528.3/819.4	403.6/637.6	284.9/447.8	214.8/343.9

Table 10: AFRIDOC-MT Pseudo-document statistics. The number of translation instances in the data AFRIDOC-MT pseudo-document splits. average and 95th percentile (average/95 percentile) of the AFRIDOC-MT document train split tokenization statistics using the different LLM tokenizers.

MADLAD-400 (Kudugunta et al., 2023) is a multilingual translation model based on the T5 architecture, covering 450 languages, including many African languages. It was trained on data collected from the CommonCrawl dataset. The dataset underwent a thorough self-audit to filter out noisy content and ensure its quality for training machine translation models.

Toucan (Elmadany et al., 2024; Adebara et al., 2024) is another multilingual but african-centric translation model based on the T5 architecture, covering 150 language pairs of African languages. It was first pre-trained on large multilingual texts covering over 500 African languages and then fine-tuned on translation task covering over 100 language pairs.

B.1.2 Large Language Models

Aya-101 (Üstün et al., 2024) is an instruction-tuned mT5 model (Xue et al., 2021) designed to handle both discriminative and generative multilingual tasks. With 13B parameters, it covers 100 languages and is capable of translating between a wide range of languages, including African languages.

Gemma2 (Gemma Team et al., 2024) is a decoder-only LLM trained on billions of tokens sourced from the web. The training data primarily consists of English-language text, but it also includes code and mathematical content. While Gemma2 has an English-centric focus, it also possesses multilingual capabilities. We evaluate the base Gemma2 model with 9B parameters, as well as its instruction-tuned version.

LLama3.1 (Dubey et al., 2024) is another decoder-only LLM trained on trillions of tokens across multiple languages. It was fine-tuned using existing instruction datasets as well as synthetically generated instruction data to create its instruction-tuned version. One advantage LLama3.1 has over other models is its context window of 128K tokens, the largest among all models considered in this work, making it particularly suitable for document-based tasks such as document-level translation. We evaluate the base LLama3.1 model with 8B parameters, as well as its instruction-tuned version.

LLaMAX3 (Lu et al., 2024) is a multilingual LLM built on the LLama3 with 8B parameters as its base. It was trained on 102 languages, including several African languages, through continued pretraining. Using an English instruction dataset (Alpaca), it was further fine-tuned to create LLaMAX3-Alpaca. We evaluated both models and compared their performance across various tasks.

B.2 Supervised Finetuning

We perform supervised fine-tuning to tailor LLMs for translation tasks. For training sentence-level MT systems, we use all parallel sentences from AFRIDOC-MT to construct the training set, enabling the LLMs to translate across multiple directions and domains. Following Zhu et al. (2024a), we augment the parallel data with translation instructions, which are randomly sampled from a predefined set of 31 MT instructions for each training example.[11] For training document-level MT systems, we follow the same process, but train on longer segments formed by concatenating multiple sentences. In finetuning, we use a learning rate of $5e^{-6}$ and an effective batch size of 64. Models are trained for only one epoch, as further training does not yield improvements and may even lead to performance degradation.

Similarly, we fine-tuned the 1.3B version of NLLB-200 for sentence and pseudo-document (with 10 sentences) translation using the Fairseq (Ott et al., 2019) codebase. We used all the training examples from 30 language directions across both domains. The model was fine-tuned for 50K steps using a learning rate of $5e^{-5}$, token batch size of 2048 and a gradient accumulation of 2. The checkpoint with the lowest validation loss was selected as the best model for evaluation.

B.3 Evaluation setup

All the models were evaluated using different tools. For example, both the NLLB-200 and M2M-100 models were evaluated with the Fairseq codebase, while Toucan and MADLAD-400 were evaluated using the Hugging Face (HF) codebase. All other LLMs, including LLama3.1 (both instruction-tuned and SFT models), Gemma, and Aya-101, were evaluated using EleutherAI LM Evaluation Harness (`lm-eval`) tool (Biderman et al., 2024). In all cases, greedy decoding was used.

All the models evaluated have different context lengths. For encoder-decoder models, M2M-100 and NLLB have a maximum sequence length of 1024 and 512 respectively. Aya-101 and MADALAD, based on the T5 architecture, do not have a pre-specified maximum sequence length, so we fixed their maximum sequence length to 1024 for all experiments involving encoder-decoder models. However, for decoder-only models, Gemma and LlamaX3 (based on LLama3) have a maximum sequence length of 8192, while LLama3.1 has a maximum sequence length of 128K. Since all the decoder-only models were evaluated using LM Eval, we used a similar setup for them, selecting the maximum length based on the specific needs of each model.

[11] We use the same instruction set as described in (Zhu et al., 2024a).

Setting	X → eng	eng → X
Sentence		
sentence	512	512
Document		
5	4096	4096
10	4096	4096
25	1024	8192 (11264)
Full	2048	16384 (32768)

Table 11: The maximum number of tokens set for decoder-only LLMs when translating between English and African languages, and vice versa. Special cases for Amharic are indicated in brackets.

Table 11 shows the maximum number of generation tokens we set when translating between English and African languages. These numbers were chosen based on the statistics from Table 10. However, for Amharic, when translating pseudo-documents with 25 sentences and full documents, there were instances exceeding the 95th percentile derived from the training statistics. Therefore, we increased the token limit specifically for Amharic.

B.4 Evaluation prompts

While the translation models we evaluated require no prompts, MADLAD-400, on the other hand, requires a prefix of the form **<2xx>** token, which is prepended to the source sentence. Here, xx indicates the target language using its language code (e.g., "sw" for Swahili). Similarly, Toucan uses just the target language ISO-693 code as prefix, which is prepended to the source sentence (e.g., "swa" for Swahili). For other models, including Aya-101, we used three different prompts for sentence-level translation and document translation experiments. The main difference between the prompts for these tasks is the explicit mention of "text" or "document" within the prompt, as shown in Table 19. For the base models Gemma2, Llama3.1, LLaMAX3, and Aya-101, we prompted them directly using the respective prompts. However, for the instruction-tuned versions of Gemma2 and Llama3.1, we used their respective chat templates. For all Alpaca-based models, including our SFT models, we used the Alpaca template.

B.5 Evaluation metrics

We evaluate translation quality with BLEU (Papineni et al., 2002) and CHRF (Popović, 2015) using SacreBLEU[12] (Post, 2018). We run significance tests using bootstrap resampling and report the 95% confidence interval for the scores, based on a sample size of 1000. We also use AfriCOMET[13] (Wang et al., 2024a) to evaluate the quality of the translation outputs. We report the CHRF scores of the best prompt for each model and language direction in the main paper, with all additional results provided in the Appendix C. For document-level experiments, we evaluated the LLMs using the same three prompts as in the sentence-level experiment. For evaluation, we used BLEU and CHRF scores but excluded AfriCOMET due to its backbone model, AfroXLM-R-L (Alabi et al., 2022; Adelani et al., 2024a), having a context length of 512 tokens. This made it impractical to compute COMET scores for document-level outputs.

B.6 GPT-4o as an evaluator for machine translation

As a proxy for human evaluation, we use GPT-4o to assess the quality of translation output, as demonstrated by (Sun et al., 2024), which shows a correlation with human judgment. Due to the cost of this task, we limited our evaluation to a few selected models, including Aya-101, GPT-3.5, GPT-4o, and LLaMAX3 fine-tuned on AfriDoc-MT sentences and pseudo-documents of 10 sentences. We compared translations performed at the sentence level and pseudo-document level in terms of fluency, content errors, and cohesion errors—specifically lexical (LE) and grammatical (GE) errors—using the same definitions as (Sun et al., 2024).

Below are the prompts used to evaluate documents using GPT-4o for fluency, content errors, and cohesion errors—specifically lexical (LE) and grammatical (GE) errors.

- **Fluency**: GPT-4o is prompted to rate the fluency of a document on a scale from 1 to 5, where 5 indicates high fluency and 1 represents low fluency. This evaluation is conducted without providing any reference document. For the final fluency score, we report the average rating across all documents. Below we provide the prompt used.

````
Please evaluate the fluency of the
    following text in <<target>>.

------

### **Instructions:**

- **Task**: Evaluate the fluency of
    the text.

- Scoring: Provide a score from 1 to
    5, where:

  - **5**: The text is **highly
      fluent**, with no grammatical
      errors, unnatural wording, or
      stiff syntax.
  - **4**: The text is **mostly
      fluent**, with minor errors
      that do not impede
      understanding.
  - **3**: The text is **moderately
      fluent**, with noticeable
      errors that may slightly
      affect comprehension.
  - **2**: The text has **low
      fluency**, with frequent
      errors that hinder
      understanding.
  - **1**: The text is **not fluent
      **, with severe errors that
      make it difficult to
      understand.
- **Explanation**: Support your
    score with specific examples to
    justify your evaluation.

------

### **Output Format:**

Provide your evaluation in the
    following JSON format:

```
{
  "Fluency": {
    "Score": "<the score>",
    "Explanation": "<your
        explanation on how you made
        the decision>"
  }
}
```

------

**Text to Evaluate:**

<<hypothesis>>
````

[12] case:mixed|eff:no| tok:13a|smooth:exp|v:2.3.1,

[13] https://huggingface.co/masakhane/africomet-stl-1.1

Model	Setup	*eng* → *X*					*X* → *eng*				
		d-CHRF↑	**Fluency↑**	**CE↓**	**LE↓**	**GE↓**	**d-CHRF↑**	**Fluency↑**	**CE↓**	**LE↓**	**GE↓**
Aya-101	Sent	$53.2_{9.3}$	$2.3_{0.9}$	$11.4_{3.0}$	$4.5_{0.5}$	$3.4_{0.2}$	$66.9_{2.1}$	$3.0_{0.3}$	$18.2_{1.3}$	$11.4_{1.2}$	$6.0_{1.9}$
	Doc10	$53.9_{1.9}$	$2.6_{0.7}$	$10.3_{3.5}$	$3.3_{0.9}$	$2.5_{0.6}$	$67.4_{1.8}$	$3.4_{0.3}$	$14.6_{0.8}$	$9.3_{0.9}$	$4.3_{0.3}$
GPT-3.5	Sent	$58.5_{12.4}$	$2.6_{2.0}$	$10.0_{6.2}$	$4.8_{3.0}$	$4.1_{2.6}$	$62.6_{7.9}$	$2.9_{0.6}$	$13.7_{1.9}$	$7.7_{1.2}$	$4.3_{0.9}$
	Doc10	$45.2_{23.3}$	$2.4_{2.1}$	$6.9_{3.5}$	$2.4_{1.4}$	$2.2_{1.4}$	$63.6_{8.8}$	$4.3_{0.4}$	$9.2_{2.1}$	$4.8_{0.6}$	$2.4_{0.4}$
LLaMAX3-SFT$_1$	Sent	$65.3_{2.7}$	$3.4_{0.2}$	$11.2_{1.5}$	$4.5_{0.4}$	$3.5_{0.1}$	$62.6_{7.9}$	$3.4_{0.5}$	$11.5_{1.6}$	$6.2_{1.9}$	$2.9_{0.1}$
	Doc10	$31.8_{2.8}$	$2.6_{0.5}$	$8.9_{0.6}$	$2.9_{0.6}$	$2.2_{0.3}$	$28.4_{2.1}$	$3.0_{0.3}$	$8.8_{0.2}$	$3.2_{0.2}$	$2.0_{0.1}$
LLaMAX3-SFT$_{10}$	Doc10	$61.9_{5.5}$	$4.0_{0.4}$	$12.4_{2.0}$	$2.8_{0.7}$	$2.0_{0.2}$	$70.9_{2.5}$	$4.4_{0.2}$	$9.0_{0.5}$	$5.2_{0.7}$	$2.5_{0.3}$
GPT-4o	Sent	$70.5_{5.0}$	$4.7_{0.2}$	$3.9_{2.2}$	$1.0_{0.5}$	$0.9_{0.5}$	$72.1_{2.8}$	$3.7_{0.4}$	$11.7_{1.8}$	$7.7_{0.8}$	$3.7_{0.9}$
	Doc10	$70.1_{5.3}$	$4.9_{0.1}$	$3.1_{1.6}$	$0.5_{0.2}$	$0.3_{0.3}$	$74.8_{2.7}$	$4.6_{0.2}$	$7.4_{3.2}$	$4.6_{1.6}$	$2.2_{0.8}$

Table 12: GPT-4o evaluation of selected models for document-level evalaution comparing sentence and document level for Tech domain and {hau, swa, zul} ⇔ en.

```
Answer:
```

- **Accuracy**: GPT-4 is prompted to identify and list the mistakes, such as incorrect translations, omissions, additions, and any other errors, by comparing the model's output to the reference translation. After identifying these errors, we count all of them and compute the average across all documents, reporting that as the content error (CE). Below is the prompt used.

```
Please evaluate the accuracy of the
    following translated text in <<
    target>> by comparing it to the
    provided reference text.

------

### **Instructions:**

- **Task**: Compare the text to the
    reference text.

- Identify Mistakes: List all
    mistakes related to accuracy.

  - Mistake Types:

    - **Wrong Translation**:
        Incorrect meaning or
        misinterpretation leading to
         wrong information.
    - **Omission**: Missing words,
        phrases, or information
        present in the reference
        text.
    - **Addition**: Extra words,
        phrases, or information not
        present in the reference
        text.
    - **Others**: Mistakes that are
        hard to define or categorize
        .

- **Note**: If the text expresses
    the same information as the
    reference text but uses
    different words or phrasing, it
    is **not** considered a mistake.

- **Provide a List**: Summarize all
    mistakes without repeating the
    exact sentences. Provide an
    empty list if there are no
    mistakes.

------

### **Output Format:**

Provide your evaluation in the
    following JSON format:

'''
{
  "Accuracy": {
    "Mistakes": [
      "<list of all mistakes in the
          text with format'Mistake
          Types: summarize the
          mistake', provide an empty
           list if there are no
          mistakes>"
    ]
  }
}
'''

------

**Reference Text:**

<<reference>>

**Text to Evaluate:**

<<hypothesis>>
```

- **Cohesion**: GPT-4 is prompted to rate cohesion-related mistakes, including lexical and grammatical errors, in the model's output, comparing it to the reference translation. We count each error individually, compute the average across the documents, and report them as lexical errors (LE) and grammatical rrrors (GE). Below is the prompt template we used.

```
 Please evaluate the cohesion of the
     following translated text in
     <<target>> by comparing it to
     the provided reference text.

------
```

```
### **Instructions:**

- **Task**: Evaluate the cohesion of
     the text.

- **Definition**: Cohesion refers to
     how different parts of a text
    are connected using language
    structures like grammar and
    vocabulary. It ensures that
    sentences flow smoothly and the
    text makes sense as a whole.

- Identify Mistakes: List all
    mistakes related to cohesion.

  - Separate the mistakes into:

    - **Lexical Cohesion Mistakes**:
         Issues with vocabulary
        usage, incorrect or missing
        synonyms, or overuse of
        certain words that disrupt
        the flow.
    - **Grammatical Cohesion
        Mistakes**: Problems with
        pronouns, conjunctions, or
        grammatical structures that
        link sentences and clauses.

- **Provide Lists**: Provide
    separate lists for lexical
    cohesion mistakes and
    grammatical cohesion mistakes.
    Provide empty lists if there are
     no mistakes.

------

### **Output Format:**

Provide your evaluation in the
    following JSON format:

```
{
  "Cohesion": {
    "Lexical Cohesion Mistakes": [
      "<list of all mistakes in the
           text one by one, provide
           an empty list if there are
            no mistakes>"
    ],
    "Grammatical Cohesion Mistakes":
         [
      "<list of all mistakes in the
           text one by one, provide
           an empty list if there are
            no mistakes>"
    ]
  }
}
```

Reference Text:

<<reference>>

Text to Evaluate:

<<hypothesis>>
```

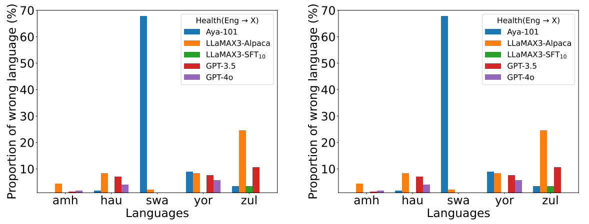

Figure 6: Rate of off-target translation (k =10).

Fluency can only have values between 1 and 5; however, the other metrics, including CE, GE, and LE, do not have a specific range and can take on any value because they are counts. Refer to (Sun et al., 2024) for more details about these metrics.

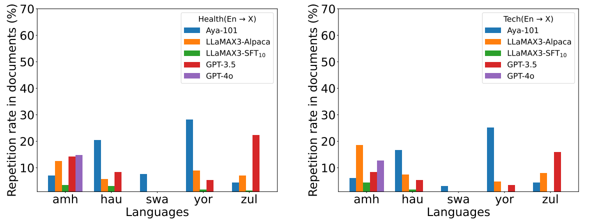

Figure 7: Word repetition rate in the pseudo-document translation (k =10).

C More experimental results

C.1 Sentence-level evaluation

Given that AFRIDOC-MT is a document-level translation dataset, and due to the limited context length of most translation models and LLMs, which makes it impossible to translate a full document at once, we opted to translate the sentences within the documents and then merge them back to form the complete document. This also serves as a baseline for document-level translation. In the main paper, we present the results for the best prompt for each language pair and model using d-CHRF. In this section, we also provide the full results on the merged documents using d-CHRF and d-BLEU in Tables 13 and 14. Furthermore, we present results for evaluating just the sentences (without merging them back into documents) using s-BLEU, s-CHRF, and s-COMET in Tables 15 and 16. Also, in Figures 17 to 20, we provide plots that summarizes some of the results in the table for few models. Although the main findings are summarized in the main draft, below are some other points we identify.

M2M-100 is not competitive Both versions of M2M-100, which was once a state-of-the-art translation model, are not competitive with other translation models such as Toucan, NLLB-200, and MADLAD-400, even when compared to models of similar sizes, across all metrics at both the sentence and document levels.

Base LLMs are not translators for African languages. Base LLMs without instruction tuning and supervised fine-tuning, such as Gemma2 and LLaMAX3, also do not show competitive translation performance. This can be explained by the fact that they are just language models with limited coverage of African languages. However, LLaMAX3, which was trained on more than 100 languages, including African languages, through continued pre-training, shows improved performance, surpassing LLama3.1-IT.

Amharic and Yorùbá are the least performing language directions. When translating from English into African languages, our results show that both Amharic and Yoruba perform the least effectively. This may be attributed to specific properties of these languages, such as the use of non-Latin script in Amharic and the use of diacritics in Yoruba, which in turn increase the tokenization rate of these languages by the different model tokenizers.

C.2 Document-level evaluation

For document-level evaluation, we split the documents into chunks of 10 sentences and translate these chunks using the different models. In Tables 17 and 18 we provide the full results on the merged pseudo-documents using d-CHRF and d-BLEU. And below are some other relevant points from the results. It is important to note that we also trained and evaluated NLLB-200 for pseudo-document translation; however, due to its 512-token maximum sequence length, it is not competitive. Nevertheless, the results still show the influence of fine-tuning. Below are other findings.

Gemma2-IT shows better translation performance. Compared to the sentence-level setup, where Gemma2-IT and LLaMAX3-Alpaca achieved similar performance on average, in the pseudo-document setup, Gemma2-IT not only outperforms LLaMAX3-Alpaca but also surpasses GPT-3.5. Although we cannot provide an exact explanation for this performance, we hypothesize that its pre-training setup might be a contributing factor.

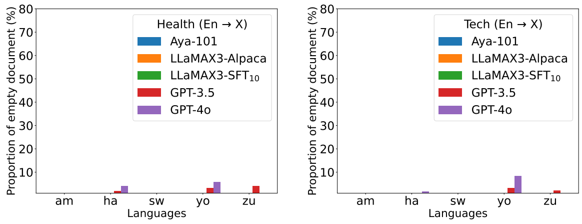

Figure 8: Proportion of empty outputs for pseudo-documents.

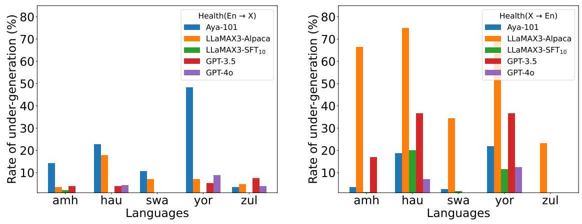

Figure 9: Rate of under-generation in pseudo-document translation (k =10)

Finetuning data has impact of translation quality. Our results show that both LLama3.1 and LLaMAX3 models, when finetuned on sentences, performed significantly worse on pseudo-document evaluations compared to the same models finetuned on pseudo-documents for both domains. All these models were trained using a similar setup, with the primary difference being the data used for finetuning.

C.3 GPT as a proxy for human evaluation

In Tables 8 and 12 We present the GPT-4o evaluation results for five models, including the GPT-4o translation outputs for both domains, evaluating translations between English and three African languages: Hausa, Swahili and Zulu due to resource constraint. The results show that GPT-4o achieves the best overall performance, demonstrating high fluency, fewer content errors, and fewer lexical and grammatical errors, which can be attributed to self-bias. However, our findings indicate that, overall, document-level translation output (pseudo-documents) are more fluent compared to sentence-level translations. Similarly, document-level translations have fewer lexical and grammatical errors, although content errors are not specifically consistent.

D More discussion and analysis

A manual inspection of the outputs of GPT-4o when used as a proxy for human evaluation in evaluating the translated documents obtained for se-

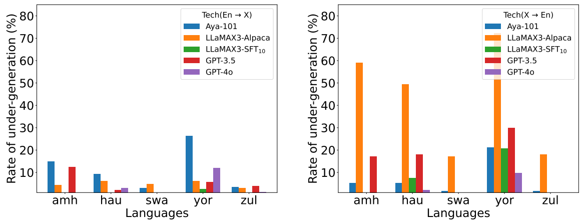

Figure 10: Rate of under-generation in pseudo-document translation (k =10)

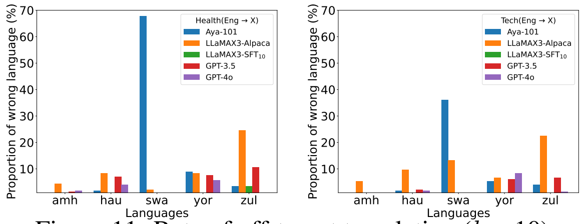

Figure 11: Rate of off-target translation (k =10)

lected LLMs and language pairs reveals several issues. These include word and phrase repetition, off-target translations, incorrect translations, and possible omissions. These issues, which are also identified in the literature as common in document-level translation with LLMs (Wu et al., 2024; Wang et al., 2024b). To gain a better understanding of some of these issues, we conducted an analysis by computing statistics on the model's pseudo-document outputs and posing specific questions.

Are the outputs generated by translation models of appropriate length? We analyzed the translation outputs comparing them to their corresponding reference translation to check wether they are, empty or if the models under-generate. Our analysis shows that all models rarely generate empty translations (refer to Figure 8). However, GPT-3.5 and GPT-4o exhibit a slight tendency to generate empty translations when translating into Yorùbá and Zulu for both domains, though this occurs rarely with a frequency of 10%. For output length, translations with lengths less than 70% of the ground truth were considered under-generated. Figures 9 and 10 shows Aya-101 under-generates more than 3% of the pseudo-documents when translating into African languages. In the other direction, LLaMAX-Alpaca shows atleast 15% under-generation into English, while other models have considerable amount of under-generation as well.

When we compare our SFT models trained on sentences and pseudo-documents with k=10, our result in Figure 13 shows that the models trained on sentences under-generates when used for long document translation.

Do LLMs generate translations in the correct target languages? We evaluate whether these models understand the task by generating outputs in the target languages using the OpenLID (Burchell et al., 2023) language identification model. Our results show that these models rarely generate outputs in the wrong language when translating to English. However, when translating to African languages, there is a higher likelihood of incorrect language translations, particularly with open models (Figure 11).

What is the effect of document length on translation quality? We compare the average d-CHRF scores obtained by selected models, including GPT-3.5/4 and LLama3.1-SFT$_k$ where k =1,5,10. The evaluation was conducted across all pseudo-document lengths: 1, 5, 10, 25, and the full length. Figure 3 shows that for translations into African languages, d-CHRF scores decrease as document length increases. A similar trend is observed for the reverse translation, except for GPT-4o, which shows an increasing trend.

What language benefits more from supervised finetuning? We focus on the sentence-level task and translated across all 30 directions for which the model was trained, evaluating both NLLB-200 (1.3B) and its fine-tuned version using d-CHRF. Figures 14 and 15 show performance improvements after supervised fine-tuning of NLLB-200 for both domains. The results shows that translating into Yorùbá, which is the direction with the lowest d-CHRF score from English among all the languages, benefited the most. One major factor contributing to this is the presence of diacritics.

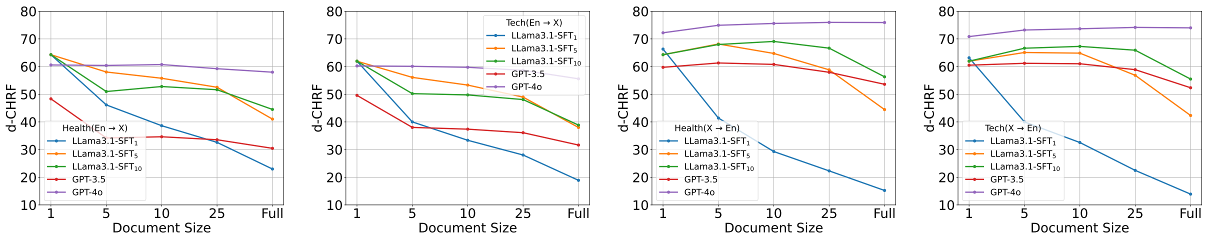

Figure 12: Average CHRF score across languages for documents of different sizes.

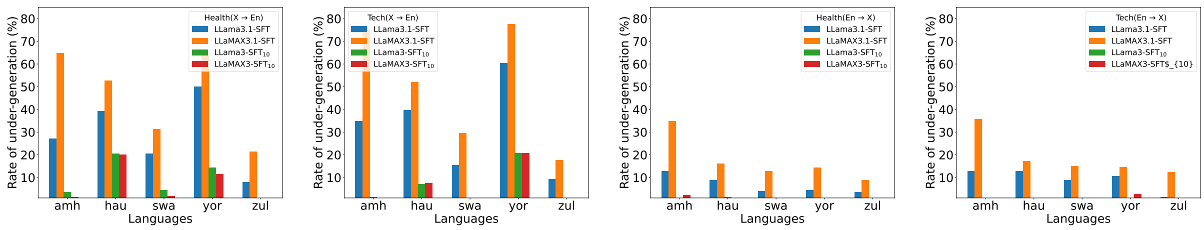

Figure 13: Rate of under-generation in our SFT models.

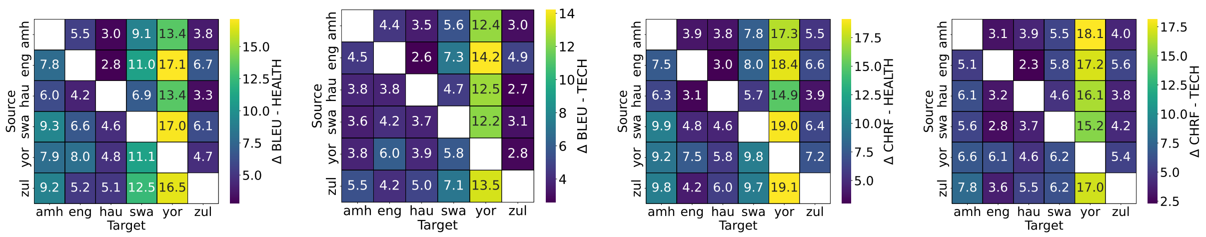

Figure 14: Change in s-BLEU and s-CHRF for sentence evaluation comparing NLLB1.3B before and after supervised finetuning on AFRIDOC-MT

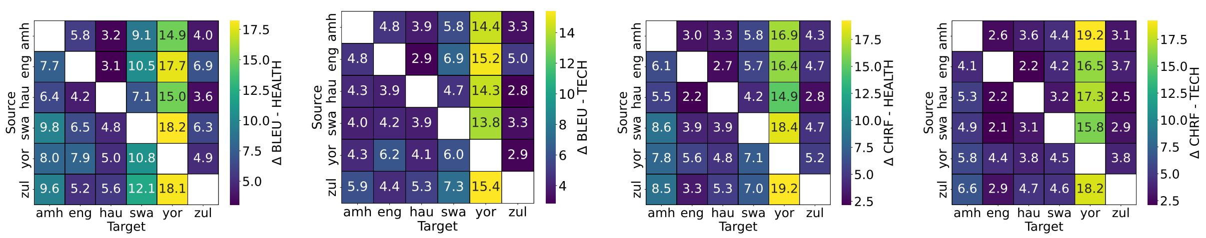

Figure 15: Change in d-BLEU and d-CHRF for sentence evaluation comparing NLLB1.3B before and after supervised finetuning on AFRIDOC-MT

Model	Size	eng → X amh	hau	swa	yor	zul	X → eng amh	hau	swa	yor	zul	AVG
						BLEU						
Encoder-Decoder												
M2M-100	0.4B	0.8	0.9	25.6	0.6	3.2	6.7	5.8	32.6	1.7	14.4	9.2
M2M-100	1.2B	2.4	8.9	37.1	2.4	6.9	15.6	13.7	42.6	4.3	23.7	15.8
NLLB-200	0.6B	18.4	26.5	42.0	10.9	19.6	33.0	30.4	45.7	32.4	42.2	30.1
Toucan	1.2B	6.6	18.7	37.3	6.4	9.4	17.4	22.4	31.9	18.1	25.2	19.3
NLLB-200	1.3B	20.0	28.6	44.9	14.0	20.7	36.3	33.1	50.0	37.1	45.9	33.1
NLLB-200	3.3B	24.2	29.7	47.1	13.2	22.2	39.0	34.7	52.7	39.1	48.4	35.0
MADLAD-400	3B	8.0	14.9	42.2	2.3	9.0	36.3	30.6	51.7	15.0	40.4	25.0
MADLAD-400	7.2B	10.5	20.3	44.8	2.4	12.2	40.3	33.7	54.8	27.3	46.6	29.3
Aya-101	13B	7.7/9.6/9.7	18.5/17.2/18.0	6.6/10.9/3.1	5.1/5.1/5.2	11.0/10.0/10.6	29.4/27.4/9.6	28.3/26.2/17.5	42.7/39.2/19.4	24.0/22.4/22.4	36.6/35.1/25.4	21.0/20.3/14.1
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	27.7	31.7	55.4	31.7	27.6	42.1	37.3	56.5	45.1	51.1	40.6
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	0.4/0.2/0.1	0.5/1.3/0.2	0.2/0.7/0.2	0.3/0.3/0.2	0.2/0.2/0.2	2.7/2.6/0.7	1.9/1.9/0.9	2.9/3.4/0.9	1.6/1.7/0.7	1.6/1.7/0.8	1.2/1.4/0.5
LLaMAX3	8B	2.8/0.1/1.8	1.6/1.8/1.2	2.7/3.5/0.6	0.3/0.3/1.3	0.9/1.0/0.8	5.6/2.6/0.6	2.0/1.9/1.0	3.0/2.7/0.6	1.6/1.4/0.8	2.5/2.1/0.9	2.3/1.7/1.0
LLama3.1-IT	8B	1.2/1.2/1.4	6.3/6.3/5.9	22.9/22.8/19.4	1.5/1.3/1.5	1.0/1.0/0.9	10.1/11.7/9.8	22.0/21.6/20.1	38.0/36.5/36.0	13.0/14.6/12.2	14.7/16.1/14.3	13.1/13.3/12.2
LLaMAX3-Alp	8B	4.9/4.9/5.0	15.3/15.2/16.0	28.2/29.8/16.2	2.5/2.4/2.6	7.3/7.3/7.7	24.1/24.2/23.4	25.8/26.9/25.5	40.9/41.6/39.0	16.3/17.1/15.8	30.2/31.4/29.7	19.6/20.1/18.1
GPT-3.5	–	1.8/0.6/0.5	6.2/1.1/1.0	45.4/45.5/44.5	2.2/0.2/0.3	6.1/1.6/2.1	6.3/7.0/5.8	11.8/11.8/12.1	46.4/45.7/45.4	12.0/13.2/11.5	20.0/22.2/20.4	15.8/14.9/14.3
GPT-4o	–	9.5/6.2/6.0	26.8/26.1/26.6	48.3/51.2/51.4	7.8/7.1/7.5	20.0/21.5/22.2	27.8/29.4/29.8	28.4/29.4/32.0	46.9/48.5/52.5	33.4/35.3/36.9	42.1/44.0/46.9	29.1/29.9/31.2
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	17.6/17.6/17.9	17.4/18.4/18.7	30.9/34.3/38.3	22.2/21.9/23.4	12.0/13.8/15.6	30.6/31.0/32.2	19.8/23.9/17.8	40.5/35.5/44.8	29.5/32.1/34.4	31.4/31.8/40.7	25.2/26.0/28.4
LLama3.1-SFT	8B	15.7/15.5/16.5	16.5/16.2/17.7	32.1/34.0/35.5	20.4/20.4/22.3	10.1/11.4/15.2	13.1/15.3/29.3	14.1/22.3/24.6	19.8/15.4/42.8	23.2/25.7/33.8	22.2/27.6/37.3	18.7/20.4/27.5
						CHRF						
Encoder-Decoder												
M2M-100	0.4B	14.9	23.4	62.7	11.5	36.7	45.6	41.2	64.4	24.9	50.2	37.6
M2M-100	1.2B	22.4	44.3	70.3	17.6	50.8	54.8	53.0	70.7	32.7	58.8	47.5
NLLB-200	0.6B	48.8	62.7	74.0	42.6	68.1	66.9	63.6	72.8	63.0	70.7	63.3
Toucan	1.2B	33.8	57.6	70.3	36.0	58.0	54.7	57.7	65.2	54.0	59.9	54.7
NLLB-200	1.3B	49.8	64.7	75.5	45.1	69.0	69.4	65.3	75.3	66.3	73.2	65.4
NLLB-200	3.3B	53.0	65.2	76.7	43.8	70.7	70.9	66.5	77.0	67.6	74.7	66.6
MADLAD-400	3B	36.5	54.4	74.2	19.1	57.1	68.9	63.8	76.1	51.4	68.9	57.0
MADLAD-400	7.2B	39.8	59.7	75.2	20.8	61.9	71.5	65.6	78.0	60.6	72.8	60.6
Aya-101	13B	32.0/36.6/36.6	55.4/56.4/55.6	35.2/44.7/28.5	30.9/31.2/29.7	58.5/58.5/58.6	64.6/63.7/23.3	61.5/61.2/48.8	70.8/69.8/43.2	57.9/57.3/55.3	66.9/67.4/53.7	53.4/54.7/43.3
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	55.9	67.4	81.3	61.5	73.7	72.4	67.5	79.2	71.8	76.5	70.7
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	14.2/13.0/1.1	14.5/23.9/9.3	9.2/18.0/8.8	5.8/9.8/3.5	12.5/15.1/10.3	34.4/34.0/16.7	22.6/23.4/17.5	23.5/27.0/17.2	23.0/23.8/16.9	19.6/20.8/16.8	17.9/20.9/11.8
LLaMAX3	8B	27.0/9.1/13.8	21.4/23.1/17.1	24.8/29.8/13.4	7.4/8.9/8.5	25.0/27.4/19.7	41.0/31.0/10.5	20.5/22.6/16.4	23.0/21.1/15.1	20.7/18.8/18.7	21.8/19.6/18.6	23.3/21.1/15.2
LLama3.1-IT	8B	19.4/19.6/19.5	45.4/45.9/43.8	63.6/63.7/57.3	18.2/17.0/19.7	28.4/28.5/28.0	51.2/53.9/50.7	59.2/59.8/58.6	68.3/69.1/66.7	50.5/53.4/49.2	51.6/54.0/51.6	45.6/46.5/44.5
LLaMAX3-Alp	8B	30.5/30.3/30.4	56.0/55.1/56.3	66.7/67.8/49.1	19.1/19.1/19.3	55.9/56.0/56.1	63.3/62.8/62.9	62.1/62.4/62.3	71.3/71.7/70.8	54.3/56.1/55.1	65.0/65.3/64.9	54.4/54.7/52.7
GPT-3.5	–	20.4/13.1/12.0	44.3/20.4/20.9	76.7/76.6/76.1	21.3/7.3/8.9	51.1/28.0/32.7	47.4/48.3/47.9	52.4/51.2/52.3	74.8/75.0/74.5	50.9/52.1/50.6	58.4/59.5/58.4	49.8/43.1/43.4
GPT-4o	–	36.7/32.4/32.3	64.2/62.4/62.9	79.1/79.8/79.8	29.3/27.2/28.4	69.0/65.6/66.4	66.7/67.2/67.1	65.8/66.0/66.5	77.0/77.5/78.1	68.0/68.9/69.1	74.1/74.7/75.1	63.0/62.2/62.6
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	46.5/46.8/46.8	61.4/62.0/62.5	66.8/70.7/73.1	56.4/56.2/57.5	60.3/65.1/67.5	64.7/65.6/66.6	53.7/58.9/48.2	69.6/63.7/73.1	60.3/63.2/64.7	60.6/61.4/70.5	60.0/61.4/63.1
LLama3.1-SFT	8B	44.5/44.1/45.6	61.0/60.8/61.8	70.1/71.0/71.5	56.1/56.1/57.0	57.5/59.6/66.8	33.2/39.1/64.3	45.4/58.8/59.5	44.2/38.8/72.1	53.4/56.2/64.8	51.7/60.5/69.0	51.7/54.5/63.2

Table 13: Performance results of various models on the sentence-level task for the Health domain, measured using document level metric d-BLEU and d-CHRF.

Model	Size	eng → X amh	hau	swa	yor	zul	X → eng amh	hau	swa	yor	zul	AVG
						BLEU						
Encoder-Decoder												
M2M-100	0.4B	1.1	1.7	22.6	1.0	4.7	7.1	10.2	29.0	2.0	15.1	9.5
M2M-100	1.2B	2.8	13.2	29.7	3.7	9.1	16.0	19.0	36.3	5.3	23.1	15.8
NLLB-200	0.6B	16.5	27.3	34.5	12.3	23.4	32.6	33.4	40.5	27.3	40.7	28.9
Toucan	1.2B	5.9	20.4	28.0	8.1	12.4	15.8	25.6	30.1	17.7	25.2	18.9
NLLB-200	1.3B	18.4	28.8	36.1	14.8	24.1	36.8	36.0	43.4	30.6	44.1	31.3
NLLB-200	3.3B	22.9	29.2	37.1	14.2	25.5	39.2	37.0	45.4	31.8	45.7	32.8
MADLAD-400	3B	7.8	16.2	22.2	2.7	11.1	35.8	34.8	43.8	16.2	38.2	22.9
MADLAD-400	7.2B	9.3	21.3	27.5	3.3	14.7	38.3	37.6	44.6	23.7	43.3	26.4
Aya-101	13B	7.8/9.1/9.0	20.8/19.4/20.8	9.2/8.9/4.8	6.3/6.3/6.6	13.2/12.6/13.2	30.7/28.7/11.4	33.3/30.7/19.3	38.7/35.9/20.6	23.4/21.6/22.5	37.4/35.3/28.8	22.1/20.8/15.7
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	23.1	31.7	43.0	29.9	29.1	41.6	39.9	47.6	36.8	48.5	37.1
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	0.3/0.2/0.1	0.7/1.4/0.3	0.3/0.4/0.2	0.3/0.3/0.2	0.3/0.3/0.2	1.9/2.4/0.5	1.8/2.0/0.8	2.3/3.2/0.6	1.5/1.6/0.6	1.4/1.5/0.6	1.1/1.3/0.4
LLaMAX3	8B	1.9/0.5/1.2	1.6/1.7/2.0	2.0/2.4/1.3	0.4/0.4/1.8	1.0/1.3/0.9	4.2/2.1/0.5	1.9/1.9/1.6	2.4/2.1/0.7	1.3/1.2/0.8	2.3/1.9/1.0	1.9/1.5/1.2
LLama3.1-IT	8B	1.3/1.2/1.2	7.6/7.7/6.9	19.7/19.4/16.1	2.0/1.8/1.9	1.2/1.3/1.2	8.0/9.1/8.2	24.6/23.4/23.0	34.0/31.7/32.2	13.1/13.9/12.3	15.2/14.3/14.2	12.7/12.4/11.7
LLaMAX3-Alp	8B	4.2/4.3/4.1	16.6/16.8/17.9	22.4/21.9/12.9	3.2/3.4/3.5	10.2/10.3/11.1	24.3/25.9/25.3	30.1/30.8/30.4	37.0/37.3/37.0	16.7/17.3/16.6	32.2/33.0/32.5	19.7/20.1/19.1
GPT-3.5	–	1.9/0.8/0.7	9.2/2.4/2.7	35.7/35.4/34.9	3.5/0.6/0.7	7.9/3.0/2.9	6.1/5.8/5.3	17.6/17.1/16.4	41.6/40.2/40.8	13.5/13.3/12.1	23.5/23.3/21.6	16.0/14.2/13.8
GPT-4o	–	7.9/5.7/5.4	28.4/27.3/27.5	40.3/39.8/40.5	7.7/7.3/7.4	26.0/25.1/25.4	31.1/29.9/30.3	37.6/35.1/37.1	46.9/42.9/46.6	32.0/30.5/31.8	46.2/43.3/45.7	30.4/28.7/29.8
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	11.8/12.2/12.3	16.6/17.1/18.5	19.9/22.0/26.1	19.1/18.9/20.9	10.2/12.9/15.3	25.9/26.2/27.9	15.8/20.1/15.1	29.8/23.1/35.4	22.0/23.7/23.6	25.6/26.3/35.2	19.7/20.3/23.0
LLama3.1-SFT	8B	10.3/10.4/11.0	14.6/15.2/17.5	20.2/20.9/24.0	18.4/17.9/20.5	8.9/10.8/14.5	8.8/9.0/26.5	12.5/19.4/24.5	19.9/14.3/35.0	16.3/17.2/28.2	22.9/24.8/33.6	15.3/16.0/23.5
						CHRF						
Encoder-Decoder												
M2M-100	0.4B	16.9	26.7	62.8	14.2	40.3	46.5	47.3	63.4	28.1	51.5	39.8
M2M-100	1.2B	24.2	50.6	68.2	20.9	52.9	56.1	57.2	67.8	36.6	58.6	49.3
NLLB-200	0.6B	47.7	64.2	71.4	41.4	70.0	67.0	65.0	70.2	60.7	69.3	62.7
Toucan	1.2B	32.0	59.5	66.1	37.1	58.5	54.0	59.9	64.1	54.3	59.6	54.5
NLLB-200	1.3B	49.3	65.7	72.3	43.0	70.3	69.5	66.8	72.0	63.0	71.5	64.3
NLLB-200	3.3B	52.2	65.4	72.8	40.1	71.6	70.9	67.7	73.2	63.9	72.5	65.0
MADLAD-400	3B	37.3	57.0	62.1	21.3	58.5	68.6	66.0	72.1	53.1	67.6	56.4
MADLAD-400	7.2B	39.7	60.6	66.2	22.8	63.5	70.5	67.8	72.3	59.0	70.9	59.3
Aya-101	13B	33.8/37.3/36.6	58.7/58.7/58.9	41.8/42.4/32.7	31.0/31.4/30.0	58.3/58.9/58.4	65.2/64.4/27.2	64.8/64.1/48.7	69.1/68.1/46.2	58.5/57.9/57.1	67.1/66.9/57.7	54.8/55.0/45.3
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	53.4	67.9	76.5	59.5	74.0	72.1	69.0	74.1	67.5	74.3	68.8
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	13.7/13.2/1.2	16.1/23.4/9.6	10.3/16.6/9.8	6.9/10.7/4.1	13.7/17.8/10.4	30.8/35.1/15.5	20.5/21.9/15.8	20.2/26.7/14.4	21.5/22.9/15.6	18.1/19.4/14.8	17.2/20.8/11.1
LLaMAX3	8B	25.5/19.4/10.7	21.1/22.2/18.5	23.0/26.9/16.0	7.9/9.6/10.7	23.8/26.7/25.0	36.2/28.3/9.9	18.8/22.6/16.7	20.4/19.8/16.8	18.8/17.4/19.1	19.9/18.0/18.9	21.5/21.1/16.2
LLama3.1-IT	8B	19.2/19.5/19.1	47.3/47.8/45.9	63.4/63.4/59.2	20.4/19.4/20.8	29.2/30.4/28.9	49.0/51.0/49.1	60.7/61.0/60.2	66.0/65.8/65.0	51.7/53.5/50.5	51.5/52.4/51.6	45.8/46.4/45.0
LLaMAX3-Alp	8B	30.1/30.2/30.3	58.5/58.1/58.9	64.9/64.0/49.4	21.7/21.8/22.0	58.0/58.0/58.6	62.9/63.4/63.0	64.7/64.9/64.6	68.8/69.1/68.9	55.6/56.5/55.8	65.4/65.7/65.4	55.1/55.2/53.7
GPT-3.5	–	22.6/16.4/15.6	49.2/29.6/31.8	72.6/72.6/72.4	23.0/12.8/14.0	53.6/35.9/35.6	47.3/47.3/47.4	56.3/56.5/56.0	71.5/71.4/71.4	53.2/54.0/52.5	59.6/59.9/58.7	50.9/45.6/45.5
GPT-4o	–	36.9/33.7/33.1	65.2/63.2/63.3	75.3/75.2/75.3	29.4/28.4/28.8	71.1/68.2/68.0	67.2/67.2/66.9	69.1/68.7/68.9	74.4/73.7/74.2	66.2/66.3/66.4	73.4/72.9/73.2	62.8/61.7/61.8
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	42.0/42.6/42.8	60.9/61.3/62.4	62.7/65.4/67.6	54.0/54.2/55.2	56.4/62.9/66.0	60.5/61.0/63.0	46.5/53.5/43.2	61.4/52.8/67.5	55.0/57.3/55.2	55.2/56.7/66.8	55.5/56.8/59.0
LLama3.1-SFT	8B	40.3/40.3/41.6	59.8/60.2/61.8	64.2/65.1/66.4	53.9/53.7/54.9	54.1/58.4/64.6	22.5/23.7/62.0	40.8/53.4/58.6	47.2/40.0/67.1	44.7/47.2/61.3	54.1/57.3/65.6	48.2/49.9/60.4

Table 14: Performance results of various models on the sentence-level task for the Tech domain, measured using document level metric d-BLEU and d-CHRF.

Model	Size	*eng* → *X* amh	hau	swa	yor	zul	*X* → *eng* amh	hau	swa	yor	zul	AVG
						BLEU						
Encoder-Decoder												
M2M-100	0.4B	0.6	0.7	24.1	0.6	2.7	5.2	4.3	30.8	1.2	12.3	8.3
M2M-100	1.2B	1.9	7.0	35.6	2.2	6.3	13.3	11.4	41.0	3.1	21.4	14.3
NLLB-200	0.6B	16.8	23.2	40.2	8.9	18.3	30.9	27.9	44.2	30.2	40.1	28.1
Toucan	1.2B	5.0	15.8	35.4	5.0	8.6	14.7	19.9	30.1	16.0	22.9	17.3
NLLB-200	1.3B	18.3	25.5	43.0	11.7	19.2	34.3	30.8	48.6	35.3	44.0	31.1
NLLB-200	3.3B	22.4	26.5	45.3	10.9	20.6	36.8	32.5	51.4	37.2	46.6	33.0
MADLAD-400	3B	7.1	12.0	40.6	2.1	8.2	34.0	28.2	50.4	12.9	38.4	23.4
MADLAD-400	7.2B	9.9	17.0	43.0	2.2	11.1	37.9	31.2	53.6	25.1	44.7	27.6
Aya-101	13B	6.7/8.4/8.6	15.5/14.9/15.2	6.0/10.2/3.0	3.8/3.8/3.9	10.2/9.6/9.8	27.3/26.3/8.7	26.1/25.4/15.7	41.3/39.7/18.5	22.0/21.5/20.4	35.0/35.0/24.1	19.4/19.5/12.8
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	26.1	28.3	54.0	28.9	25.9	39.8	34.9	55.3	43.3	49.2	38.6
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	0.2/0.1/0.0	0.3/0.7/0.1	0.2/0.4/0.1	0.2/0.2/0.2	0.2/0.1/0.1	1.8/1.8/0.3	1.6/1.6/0.5	2.6/3.0/0.6	1.2/1.2/0.4	1.1/1.2/0.4	0.9/1.0/0.3
LLaMAX3	8B	2.1/0.1/1.3	1.1/1.3/0.8	2.4/3.0/0.5	0.3/0.3/1.1	0.7/0.8/0.6	4.5/1.7/0.5	1.7/1.3/0.6	2.7/2.3/0.5	1.3/1.0/0.5	2.2/1.7/0.6	1.9/1.3/0.7
LLama3.1-IT	8B	0.9/0.9/0.8	4.6/4.7/4.2	21.4/21.3/18.0	1.1/0.9/1.0	0.8/0.8/0.7	7.7/8.9/7.3	19.4/19.1/17.7	36.7/35.7/34.7	10.7/12.2/10.1	12.1/13.3/11.8	11.5/11.8/10.6
LLaMAX3-Alp	8B	4.1/4.1/4.1	12.7/12.3/13.2	26.9/28.5/15.1	2.4/2.3/2.4	6.7/6.7/7.0	21.5/21.6/20.9	23.4/24.4/23.3	39.7/40.4/37.8	13.8/14.4/13.2	28.1/29.3/27.5	17.9/18.4/16.4
GPT-3.5	–	1.4/0.4/0.3	4.4/0.8/0.7	43.6/43.6/42.8	1.9/0.2/0.2	5.3/1.4/1.8	4.3/4.4/3.6	9.5/9.3/9.2	45.5/45.3/44.5	10.2/10.8/9.3	18.3/19.9/18.0	14.4/13.6/13.0
GPT-4o	–	8.4/5.0/5.0	24.8/23.4/23.5	48.3/49.7/49.9	7.0/6.2/6.6	19.8/20.1/20.7	26.8/27.6/27.8	27.9/28.7/30.1	48.3/49.6/51.8	33.6/35.0/35.7	42.9/44.2/45.7	28.8/28.9/29.7
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	16.2/16.1/16.3	13.6/14.5/14.7	29.2/32.8/36.0	19.2/18.8/20.0	11.1/12.8/14.0	27.4/27.7/28.8	16.9/20.7/15.4	38.3/33.5/42.1	27.1/29.6/31.9	29.0/29.3/37.7	22.8/23.6/25.7
LLama3.1-SFT	8B	14.6/14.3/14.9	13.3/12.9/13.9	31.3/33.0/33.3	18.1/17.9/19.2	9.4/10.7/13.6	11.3/13.3/25.8	12.0/19.3/21.3	18.6/14.4/40.4	21.4/23.8/31.3	20.7/25.9/34.3	17.1/18.6/24.8
						CHRF						
Encoder-Decoder												
M2M-100	0.4B	6.8	11.6	51.7	7.5	19.7	30.8	25.0	55.4	13.2	35.9	25.8
M2M-100	1.2B	13.9	28.9	61.7	13.4	33.8	41.2	37.0	63.6	18.6	46.2	35.8
NLLB-200	0.6B	41.6	49.7	66.1	30.9	56.5	57.9	52.2	66.4	52.1	63.2	53.7
Toucan	1.2B	23.7	43.3	61.1	24.2	42.4	41.4	44.8	56.4	39.8	48.1	42.5
NLLB-200	1.3B	42.6	52.2	68.2	34.0	57.7	61.1	54.6	69.7	56.6	66.3	56.3
NLLB-200	3.3B	46.3	52.9	69.5	32.6	59.8	62.9	56.2	71.8	58.1	68.2	57.8
MADLAD-400	3B	28.3	39.7	66.3	15.1	42.2	60.4	53.0	70.7	35.5	60.5	47.2
MADLAD-400	7.2B	32.0	45.6	67.5	15.4	47.5	63.6	55.3	73.0	47.5	65.7	51.3
Aya-101	13B	23.6/28.0/28.0	40.3/42.1/41.0	25.6/33.5/19.4	17.7/18.2/17.7	43.6/43.9/43.8	54.6/54.3/18.0	50.0/50.3/37.2	63.8/63.5/35.9	44.0/44.1/41.6	58.0/59.4/44.4	42.1/43.7/32.7
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	50.1	55.2	76.2	52.4	64.3	65.0	57.7	74.5	64.1	70.5	63.0
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	4.8/4.3/0.4	6.1/11.6/5.7	5.5/8.2/5.6	2.6/3.6/2.9	5.7/5.8/5.9	21.7/21.2/8.0	16.6/17.3/9.5	19.3/21.7/9.8	14.9/15.5/9.0	12.5/13.5/9.1	11.0/12.3/6.6
LLaMAX3	8B	17.1/5.0/6.5	14.3/15.8/6.7	19.7/23.6/5.4	5.5/6.3/3.8	16.9/17.9/7.1	29.2/12.3/5.6	15.7/11.7/4.1	20.0/17.1/9.0	14.0/12.1/7.1	17.7/15.2/6.7	17.0/13.7/6.2
LLama3.1-IT	8B	8.8/8.9/8.7	28.7/29.0/26.5	50.9/51.2/43.2	8.5/7.9/8.7	14.9/14.8/14.1	33.4/35.7/32.7	44.7/45.4/44.0	59.6/60.6/57.8	33.6/35.7/32.1	34.2/36.4/34.5	31.7/32.6/30.2
LLaMAX3-Alp	8B	20.8/20.7/20.8	40.5/39.5/41.2	56.0/57.3/36.8	15.4/15.3/15.4	38.9/38.8/39.1	50.9/50.5/50.3	49.3/49.7/49.4	63.7/64.1/62.9	37.3/38.8/37.8	53.5/54.1/53.3	42.6/42.9/40.7
GPT-3.5	–	10.9/6.3/5.8	27.2/12.2/12.2	69.3/69.3/68.5	12.9/4.0/4.6	32.2/16.8/19.8	26.8/28.3/26.9	33.9/33.3/33.0	69.0/69.4/68.4	32.5/33.8/31.8	44.0/45.0/43.1	35.9/31.8/31.4
GPT-4o	–	28.2/24.7/24.6	52.4/49.9/50.3	74.0/74.2/74.1	22.2/20.4/21.2	58.6/53.8/54.6	57.2/57.5/57.3	56.3/56.4/56.4	73.3/73.7/73.5	59.5/60.4/60.3	68.7/69.1/68.9	55.1/54.0/54.1
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	38.2/38.4/38.4	44.3/45.0/46.0	55.7/60.3/63.4	43.9/43.7/45.3	44.8/50.1/53.3	52.7/53.6/54.9	39.7/44.6/36.1	60.4/54.3/64.6	49.4/52.1/54.0	50.1/50.7/60.3	47.9/49.3/51.6
LLama3.1-SFT	8B	35.7/35.3/36.7	44.9/44.3/45.0	60.6/61.3/61.1	44.2/43.9/44.9	42.6/44.5/52.4	24.0/28.9/51.8	32.7/44.1/45.2	35.9/30.9/63.2	42.6/45.2/53.6	40.9/48.8/58.0	40.4/42.7/51.2
						COMET						
Encoder-Decoder												
M2M-100	0.4B	19.6	20.1	58.3	21.5	26.7	43.9	32.5	66.0	23.5	42.0	35.4
M2M-100	1.2B	29.2	35.4	70.0	37.4	42.6	55.4	47.9	73.3	26.4	53.5	47.1
NLLB-200	0.6B	70.5	69.6	75.8	71.5	73.4	73.9	68.7	77.2	68.2	72.6	72.2
Toucan	1.2B	56.3	63.3	72.6	64.1	62.5	62.1	62.1	70.7	56.9	60.0	63.1
NLLB-200	1.3B	71.7	71.2	77.3	72.9	74.2	76.0	70.5	78.9	71.4	74.5	73.9
NLLB-200	3.3B	72.8	70.9	77.5	70.8	74.8	77.2	71.3	79.7	72.9	75.5	74.3
MADLAD-400	3B	65.1	62.7	75.9	49.5	65.8	76.6	69.8	79.5	52.8	71.2	66.9
MADLAD-400	7.2B	69.1	67.4	77.1	55.0	69.2	78.2	71.9	80.2	65.6	74.9	70.9
Aya-101	13B	53.7/62.0/61.2	62.0/64.2/62.4	31.7/44.2/46.3	50.0/50.2/46.8	62.8/63.7/63.8	73.5/73.0/49.7	67.6/68.0/60.0	76.1/75.0/62.1	62.0/62.8/59.3	67.9/70.2/58.6	60.7/63.4/57.0
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	75.4	74.0	80.2	78.9	75.7	78.4	72.6	80.5	75.8	76.6	76.8
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
Llama3.1	8B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLaMAX3	8B	34.3/28.2/28.1	27.1/27.8/23.9	31.8/43.7/25.9	22.9/27.4/22.9	32.6/39.6/26.2	36.1/31.2/18.7	34.5/31.2/17.3	31.9/42.7/26.3	28.8/37.1/19.2	30.0/39.7/22.5	31.0/34.9/23.1
LLama3.1-IT	8B	20.3/20.2/20.0	43.1/42.8/39.4	61.2/61.7/56.0	30.8/29.5/31.9	24.4/24.2/24.2	52.9/56.1/51.2	61.7/61.8/60.7	71.8/70.0/70.7	49.7/53.4/47.0	47.1/49.9/46.0	46.3/47.0/44.7
LLaMAX3-Alp	8B	45.9/46.0/45.8	60.9/60.5/61.6	68.9/69.7/57.9	45.2/45.2/45.1	58.6/58.8/58.3	71.6/71.8/71.4	68.3/69.0/68.7	75.9/76.5/75.6	57.0/60.5/58.2	67.5/68.5/67.2	62.0/62.7/61.0
GPT-3.5	–	22.4/22.9/21.9	35.0/34.7/34.6	78.0/78.1/77.0	36.2/33.2/34.9	43.2/41.1/41.6	44.4/46.9/42.9	51.1/51.3/48.5	78.2/78.5/77.1	50.3/53.3/47.9	57.4/59.1/55.6	49.6/49.9/48.2
GPT-4o	–	55.5/56.5/56.5	71.1/68.1/68.9	79.6/80.1/80.2	54.3/51.5/52.1	72.6/68.0/68.9	73.5/74.6/74.3	71.0/71.3/71.7	78.5/79.4/80.1	71.9/73.5/73.0	73.6/75.1/75.3	70.2/69.8/70.1
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	66.8/67.3/66.5	67.2/67.5/67.2	65.6/68.3/71.5	74.5/74.6/75.1	57.7/63.1/66.8	71.5/72.4/73.5	59.0/63.1/56.4	72.5/68.0/76.2	62.9/66.1/68.1	61.5/62.3/71.7	65.9/67.3/69.3
LLama3.1-SFT	8B	61.1/61.9/62.5	63.9/64.4/66.6	66.0/67.4/68.5	73.7/73.9/74.3	53.1/55.4/64.2	48.9/52.0/70.8	53.0/62.3/63.3	55.1/52.6/74.7	54.1/57.5/67.7	52.4/59.3/68.8	58.1/60.7/68.1

Table 15: Performance results of various models on the sentence-level task for the Health domain, measured using sentence level metric s-BLEU, s-CHRF, and s-COMET.

Model	Size	eng → X					X → eng					AVG
		amh	hau	swa	yor	zul	amh	hau	swa	yor	zul	
BLEU												
Encoder-Decoder												
M2M-100	0.4B	0.9	1.2	20.9	0.9	4.0	5.5	8.2	26.7	1.4	12.9	8.3
M2M-100	1.2B	2.6	10.9	27.6	3.4	8.2	13.6	16.3	34.0	4.0	20.7	14.1
NLLB-200	0.6B	15.3	24.3	32.3	9.7	22.0	30.7	30.7	38.2	24.6	38.5	26.6
Toucan	1.2B	4.8	17.6	25.8	6.1	11.4	13.2	22.8	27.7	15.1	22.8	16.7
NLLB-200	1.3B	17.2	25.9	33.8	11.9	22.6	34.9	33.5	41.3	28.1	42.0	29.1
NLLB-200	3.3B	21.8	26.4	34.9	11.5	24.2	37.3	34.4	43.3	29.2	43.7	30.7
MADLAD-400	3B	7.0	13.7	20.3	2.4	9.8	33.4	32.2	41.6	13.7	36.0	21.0
MADLAD-400	7.2B	8.8	18.2	25.4	2.9	13.4	36.1	35.0	42.3	20.9	41.2	24.4
Aya-101	13B	6.8/7.9/7.8	18.1/17.6/18.0	8.5/8.4/4.5	4.9/5.0/5.2	12.2/12.1/12.3	28.5/27.9/10.6	31.2/30.3/17.3	36.8/36.2/19.1	21.0/20.5/19.9	35.5/35.2/26.9	20.3/20.1/14.2
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	21.7	28.5	41.0	26.1	27.5	39.4	37.3	45.5	34.1	46.2	34.7
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	0.2/0.1/0.0	0.4/0.8/0.2	0.2/0.3/0.2	0.2/0.2/0.2	0.2/0.2/0.2	1.3/1.7/0.2	1.6/1.7/0.5	2.0/2.9/0.4	1.1/1.2/0.3	1.0/1.1/0.3	0.8/1.0/0.3
LLaMAX3	8B	1.4/0.3/0.8	1.2/1.3/1.5	1.7/2.0/1.1	0.3/0.3/1.4	0.9/1.0/0.7	3.5/1.4/0.4	1.6/1.3/1.2	2.1/1.8/0.5	1.1/0.8/0.6	2.0/1.6/0.7	1.6/1.2/0.9
LLama3.1-IT	8B	1.0/0.9/0.9	5.8/6.1/5.3	17.8/17.7/14.6	1.4/1.3/1.3	1.1/1.1/1.0	5.9/6.8/6.0	22.1/21.1/20.6	32.0/30.4/30.1	10.7/11.3/9.9	12.5/11.8/11.6	11.0/10.8/10.1
LLaMAX3-Alp	8B	3.7/3.8/3.6	14.0/14.2/15.2	20.8/20.3/11.7	2.9/3.1/3.3	9.3/9.4/10.3	21.9/23.4/22.8	27.8/28.5/28.2	35.2/35.5/35.4	13.9/14.4/13.8	30.0/30.9/30.4	18.0/18.4/17.5
GPT-3.5	–	1.5/0.6/0.5	6.9/1.8/1.9	33.5/33.3/32.9	2.9/0.5/0.5	7.0/2.5/2.5	3.8/3.7/3.2	14.8/14.7/13.6	40.0/39.6/39.2	10.7/11.1/9.6	21.1/21.6/19.3	14.2/12.9/12.3
GPT-4o	–	7.0/4.9/4.6	25.6/24.7/24.7	38.4/38.1/38.6	6.6/6.3/6.4	24.8/24.1/24.1	29.0/28.6/28.2	35.4/34.6/35.1	45.2/43.5/45.0	29.8/29.6/29.7	44.6/43.4/44.1	28.6/27.8/28.1
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	10.6/10.8/11.0	13.3/13.8/14.7	18.1/20.1/23.4	15.3/15.2/16.6	9.4/11.9/13.7	22.9/23.2/24.7	13.7/17.8/13.2	27.2/21.2/32.3	19.4/20.9/20.8	23.6/24.2/32.2	17.4/17.9/20.3
LLama3.1-SFT	8B	9.6/9.5/9.7	12.1/12.4/13.7	19.1/19.6/21.4	15.5/14.8/16.3	8.3/10.1/13.1	7.6/7.9/23.2	11.1/17.3/21.6	18.4/13.2/32.0	14.5/15.5/25.1	21.3/23.2/30.5	13.7/14.4/20.7
CHRF												
Encoder-Decoder												
M2M-100	0.4B	8.9	14.9	50.3	10.1	22.7	31.7	31.1	52.9	15.6	36.7	27.5
M2M-100	1.2B	16.4	36.0	57.4	16.7	35.6	42.5	42.3	58.6	21.7	45.5	37.3
NLLB-200	0.6B	41.1	51.9	61.7	29.6	58.3	58.1	53.8	62.0	47.8	60.9	52.5
Toucan	1.2B	22.5	45.6	55.4	24.9	43.3	40.0	47.3	53.9	38.9	47.4	41.9
NLLB-200	1.3B	42.8	53.8	63.0	31.6	58.7	61.4	56.4	64.4	51.0	63.8	54.7
NLLB-200	3.3B	46.3	53.7	63.7	29.9	60.5	63.1	57.4	65.8	52.0	64.9	55.7
MADLAD-400	3B	29.1	43.0	51.5	16.6	43.6	60.0	55.6	64.6	36.8	58.3	45.9
MADLAD-400	7.2B	32.2	46.7	54.9	17.1	49.1	62.6	58.0	64.9	44.5	62.7	49.3
Aya-101	13B	25.8/29.2/28.5	44.6/45.5/45.0	31.1/31.9/22.7	19.1/19.8/19.7	43.2/44.5/43.5	55.5/55.3/21.8	54.0/54.4/38.1	60.7/60.7/37.9	44.0/44.1/42.5	57.9/58.7/47.7	43.6/44.4/34.7
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	47.9	56.1	68.8	48.8	64.3	64.5	59.6	67.2	57.1	67.4	60.2
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLama3.1	8B	4.7/4.3/0.4	7.4/12.1/5.9	6.0/5.6/6.1	3.4/4.4/3.2	5.9/6.2/6.0	18.7/21.4/6.8	15.5/16.5/8.8	16.2/21.1/8.6	14.1/14.9/8.3	11.7/12.7/8.3	10.3/11.9/6.2
LLaMAX3	8B	16.6/11.9/4.3	14.9/15.5/8.5	17.7/20.2/7.2	6.0/6.8/5.5	16.4/18.1/9.0	25.8/11.4/5.5	14.7/10.6/5.6	17.1/14.5/7.7	12.8/11.0/8.1	16.0/13.9/5.8	15.8/13.4/6.7
LLama3.1-IT	8B	8.8/8.9/8.5	30.6/30.9/28.7	49.0/49.1/44.2	10.3/9.9/10.2	15.4/16.2/15.1	30.8/32.5/30.8	46.5/46.6/45.9	55.8/55.8/54.5	34.0/35.0/32.6	34.0/34.5/33.8	31.5/31.9/30.4
LLaMAX3-Alp	8B	20.9/21.0/20.9	43.3/43.0/44.3	52.4/51.2/36.0	17.4/17.5/17.7	40.6/40.8/41.6	50.6/51.4/51.0	52.4/52.7/52.4	59.6/59.9/59.8	37.9/38.9/38.1	53.9/54.5/54.1	42.9/43.1/41.6
GPT-3.5	–	12.4/8.4/8.0	31.8/19.0/20.0	63.4/63.4/63.0	15.4/7.9/8.4	35.1/22.3/22.3	26.4/27.1/26.2	38.4/38.9/37.7	63.8/64.3/63.5	33.8/35.4/33.2	45.0/45.7/43.9	36.6/33.2/32.6
GPT-4o	–	28.6/26.1/25.4	53.5/51.5/51.5	67.2/67.2/67.3	22.3/21.4/21.4	60.0/56.5/56.4	57.3/57.7/57.0	59.8/60.0/59.6	67.7/68.1/67.5	55.0/56.0/55.3	66.2/66.4/66.0	53.7/53.1/52.7
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	33.1/33.7/33.9	44.3/44.6/45.6	48.4/51.7/54.4	39.6/39.9/41.0	40.2/46.2/49.8	47.9/48.3/50.6	34.7/40.5/32.5	49.9/42.0/56.6	42.2/44.1/42.8	44.2/45.4/55.3	42.4/43.6/46.3
LLama3.1-SFT	8B	31.5/31.2/32.4	43.8/44.1/44.9	50.9/52.2/52.5	40.6/40.1/40.9	38.6/42.5/48.5	16.5/17.6/48.9	30.4/40.2/44.7	37.3/31.2/55.8	34.3/36.0/47.9	42.4/45.2/53.4	36.6/38.0/47.0
COMET												
Encoder-Decoder												
M2M-100	0.4B	23.4	22.5	58.0	22.1	29.1	46.0	39.4	64.9	28.2	44.8	37.8
M2M-100	1.2B	34.2	42.2	67.1	37.7	42.9	57.7	54.4	70.4	32.1	54.4	49.3
NLLB-200	0.6B	69.1	69.5	72.7	70.0	72.0	72.8	69.3	74.1	66.5	71.0	70.7
Toucan	1.2B	54.7	63.1	67.2	64.3	61.4	60.7	64.3	68.8	58.4	60.3	62.3
NLLB-200	1.3B	69.4	70.9	73.1	70.2	72.8	75.1	71.3	75.6	69.1	72.6	72.0
NLLB-200	3.3B	71.2	70.2	73.4	66.6	73.2	76.0	71.7	76.0	70.3	73.2	72.2
MADLAD-400	3B	65.0	62.3	64.7	50.6	63.8	75.9	71.5	76.2	56.3	69.9	65.6
MADLAD-400	7.2B	67.8	64.9	66.5	56.7	68.3	77.4	73.6	76.5	65.4	72.9	69.0
Aya-101	13B	56.9/63.4/61.6	63.7/65.8/64.5	36.7/39.6/47.5	51.7/52.7/48.8	60.6/63.2/62.5	73.2/72.3/51.4	70.0/70.4/60.9	73.4/72.8/62.9	64.0/64.0/62.7	68.4/69.6/62.7	61.9/63.4/58.5
SFT on AfriDoc-MT												
NLLB-SFT	1.3B	74.1	73.3	76.4	78.1	73.9	77.8	74.3	77.4	73.9	75.9	75.5
Decoder-only												
Gemma2	9B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
Llama3.1	8B	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0	0.0/0.0/0.0
LLaMAX3	8B	33.8/32.3/26.1	29.6/28.1/24.3	33.4/41.9/26.3	25.8/29.5/22.7	33.2/41.5/27.2	35.3/30.2/18.7	37.9/30.1/17.9	34.4/39.6/24.1	31.2/36.6/20.2	32.6/38.9/21.9	32.7/34.9/23.0
LLama3.1-IT	8B	20.9/21.3/20.9	43.3/42.7/40.4	60.2/59.9/56.0	31.1/30.4/30.9	25.9/26.3/25.7	49.4/51.7/48.1	62.2/61.1/61.2	69.4/65.2/68.6	51.1/52.8/48.8	46.5/47.1/45.4	46.0/45.8/44.6
LLaMAX3-Alp	8B	47.0/47.2/47.0	61.6/61.2/62.2	66.0/65.2/56.0	45.2/45.5/45.1	58.4/58.6/58.6	71.0/71.6/71.0	70.3/70.7/70.1	73.8/74.1/73.8	59.0/61.4/59.6	67.5/68.1/67.3	62.0/62.4/61.1
GPT-3.5	–	25.8/26.3/25.3	40.8/41.1/39.7	74.8/74.9/73.6	38.0/36.8/37.9	46.6/43.4/44.3	45.7/48.5/44.6	55.7/56.8/54.1	75.3/75.2/74.4	53.4/55.9/51.4	59.5/60.5/58.1	51.6/51.9/50.3
GPT-4o	–	57.5/58.4/58.5	71.4/69.4/69.1	77.4/77.1/77.2	53.6/51.6/51.9	72.7/68.6/68.9	74.0/73.7/73.7	74.9/74.1/74.6	77.6/76.5/77.5	72.0/72.5/72.0	74.6/73.6/74.1	70.6/69.5/69.8
SFT on AfriDoc-MT												
LLaMAX3-SFT	8B	62.5/63.0/62.3	64.4/64.7/65.1	60.6/62.5/65.5	72.2/72.7/73.9	52.5/58.1/62.8	67.9/68.6/70.5	55.2/59.7/54.4	66.4/60.2/71.9	58.1/60.8/59.1	56.3/57.6/68.3	61.6/62.8/65.4
LLama3.1-SFT	8B	56.0/56.5/56.9	59.8/60.8/64.0	58.9/61.3/62.1	72.0/72.0/73.2	47.3/51.4/59.0	41.5/41.6/68.2	50.5/57.7/62.8	54.5/50.7/70.1	46.8/48.7/65.8	52.6/55.2/65.5	54.0/55.6/64.8

Table 16: Performance results of various models on the sentence-level task for the Tech domain, measured using sentence level metric s-BLEU, s-CHRF, and s-COMET.

Model	Size	*eng → X*					*X → eng*					AVG
		amh	hau	swa	yor	zul	amh	hau	swa	yor	zul	
						BLEU						
Encoder-Decoder												
Toucan	1.2B	2.6	9.3	17.4	3.2	4.5	8.6	8.0	18.1	8.2	12.4	9.2
NLLB-200	1.3B	4.7	8.0	13.7	2.7	8.2	6.1	10.7	20.8	9.9	16.1	10.1
NLLB-200	3.3B	5.2	5.6	14.2	2.3	7.4	12.1	16.0	26.9	12.7	23.7	12.6
MADLAD-400	3B	5.9	8.0	17.0	1.5	5.7	31.5	30.9	50.8	14.2	38.7	20.4
MADLAD-400	7.2B	1.4	5.5	13.9	1.5	4.3	20.4	12.5	41.7	4.4	17.9	12.4
Aya-101	13B	6.4/6.8/6.1	12.4/15.4/12.7	10.4/5.5/3.5	2.3/2.8/2.6	10.3/10.3/9.7	28.2/28.2/7.2	30.2/29.8/16.9	43.4/43.2/24.0	26.0/25.8/20.4	39.7/39.5/34.9	20.9/20.7/13.8
SFT on AfriDoc-MT (sentence)												
NLLB-SFT	1.3B	7.9	13.5	26.0	6.9	13.5	13.5	15.3	26.0	15.4	22.6	16.1
SFT on AfriDoc-MT (pseudo-document with 10)												
NLLB	1.3B	8.7	13.4	25.9	6.5	13.6	20.8	20.0	30.1	19.0	26.4	18.4
Decoder-only												
Gemma2-IT	9B	0.2/0.2/0.2	10.2/8.5/7.9	21.3/23.7/18.3	0.2/0.2/0.2	0.4/0.4/0.4	8.5/9.7/6.0	21.6/22.9/18.8	37.2/40.2/33.6	12.5/14.7/9.4	24.8/27.6/21.7	13.7/14.8/11.6
LLama3.1-IT	8B	0.1/0.1/0.1	0.6/0.6/0.4	7.9/10.7/6.8	0.2/0.2/0.1	0.1/0.1/0.1	4.1/5.2/5.1	19.3/20.8/4.0	32.0/35.6/2.3	7.1/9.2/6.2	11.3/11.6/8.2	8.3/9.4/3.3
LLaMAX3-Alp	8B	0.7/0.6/0.6	3.0/3.1/3.2	6.1/7.3/6.3	0.4/0.4/0.3	1.0/1.1/1.1	6.3/5.0/7.5	14.1/11.5/12.4	25.5/25.2/25.2	2.6/2.6/2.3	8.7/11.8/10.2	6.8/6.9/6.9
GPT-3.5	–	0.4/0.5/0.4	1.1/1.2/1.3	45.5/45.1/45.2	0.2/0.3/0.3	1.6/1.9/1.9	4.2/6.1/3.7	16.1/16.0/15.7	51.6/51.5/51.5	15.9/15.8/14.8	25.7/27.1/26.6	16.2/16.5/16.1
GPT-4o	–	6.3/6.2/6.8	27.1/27.3/27.4	52.4/52.9/52.6	7.4/7.4/8.3	22.6/22.4/22.1	35.4/35.2/35.6	37.5/38.1/38.1	57.8/57.9/58.2	46.0/45.6/46.0	52.5/53.0/53.0	34.5/34.6/34.8
SFT on AfriDoc-MT (sentence)												
LLaMAX3-SFT	8B	4.5/4.1/4.6	2.9/2.3/2.5	7.6/7.3/9.0	4.9/5.0/5.7	2.8/2.2/3.0	2.8/2.5/3.0	2.4/2.0/2.6	6.7/4.2/5.4	4.2/3.2/5.9	6.5/4.2/6.4	4.5/3.7/4.8
LLama3.1-SFT	8B	3.7/3.0/3.8	3.5/2.8/3.3	11.8/13.3/12.2	5.4/4.8/4.9	4.1/3.1/4.1	2.0/2.4/3.2	2.3/1.8/3.2	5.1/5.6/7.0	3.8/3.2/5.6	3.5/3.7/5.0	4.5/4.4/5.2
SFT on AfriDoc-MT (pseudo-document with 10)												
LLaMAX3-SFT	8B	10.8/9.5/10.0	10.6/10.3/11.9	35.6/34.0/39.9	18.5/15.8/17.9	9.9/9.4/8.9	29.4/28.9/28.0	34.7/30.1/33.4	51.6/51.0/54.1	44.2/37.1/44.4	47.1/46.5/47.3	29.2/27.3/29.6
LLama3.1-SFT	8B	4.8/4.9/5.0	8.0/10.0/10.2	26.8/24.6/26.2	16.4/15.8/15.3	5.6/5.8/6.7	23.2/19.4/29.8	27.1/19.7/23.9	22.9/25.9/46.8	24.3/29.0/37.5	37.1/26.7/42.7	19.6/18.2/24.4
						CHRF						
Encoder-Decoder												
Toucan	1.2B	18.9	36.5	44.4	23.0	38.5	41.1	42.0	45.2	39.7	43.3	37.2
NLLB-200	1.3B	25.0	35.5	40.4	19.5	38.8	30.7	37.1	46.9	34.7	42.6	35.1
NLLB-200	3.3B	25.6	30.4	40.2	18.4	35.4	39.7	44.5	53.6	38.2	50.7	37.7
MADLAD-400	3B	27.5	40.2	46.6	15.1	43.6	63.3	62.5	74.4	44.2	66.6	48.4
MADLAD-400	7.2B	5.3	30.6	39.8	13.4	26.1	47.2	36.2	64.5	17.2	41.2	32.1
Aya-101	13B	27.0/28.7/25.9	41.9/48.5/43.2	34.7/28.8/25.6	17.1/18.7/18.0	54.2/54.9/52.7	61.6/61.1/16.1	62.3/62.0/44.7	71.2/71.0/48.1	56.1/55.9/46.1	69.0/68.9/63.8	49.5/49.8/38.4
SFT on AfriDoc-MT (sentence)												
NLLB-SFT	1.3B	30.2	42.8	52.4	28.4	47.3	42.1	43.8	52.4	42.6	50.3	43.2
SFT on AfriDoc-MT (pseudo-document with 10)												
NLLB	1.3B	31.2	42.4	52.2	27.7	47.1	50.6	48.7	55.9	47.4	53.5	45.7
Decoder-only												
Gemma2-IT	9B	6.1/6.5/6.0	37.0/34.6/30.1	49.8/52.9/46.4	6.4/6.4/6.2	11.6/12.0/11.9	35.0/36.5/30.8	50.3/51.8/46.8	62.1/65.0/58.4	41.0/44.8/35.9	53.1/56.1/49.3	35.3/36.7/32.2
LLama3.1-IT	8B	7.4/7.5/7.4	14.0/13.8/12.2	37.5/43.2/27.7	6.4/5.6/4.9	8.3/8.7/8.6	23.8/23.3/21.9	46.9/49.3/19.7	59.0/62.8/16.8	29.0/31.7/23.1	33.0/34.0/27.0	26.5/28.0/16.9
LLaMAX3-Alp	8B	11.4/11.1/11.2	28.9/28.6/28.5	35.9/40.4/32.5	9.2/8.9/8.4	22.1/22.3/23.6	28.9/28.0/29.2	41.7/39.2/41.1	54.1/51.9/55.4	23.5/23.3/22.3	37.7/40.5/39.9	29.3/29.4/29.2
GPT-3.5	–	11.3/11.3/11.6	22.0/22.4/23.1	75.9/75.6/76.1	9.1/8.9/10.1	27.7/29.1/29.2	37.9/41.6/38.0	52.7/52.7/52.4	77.7/77.6/77.7	51.7/51.1/50.9	59.7/61.1/60.8	42.6/43.1/43.0
GPT-4o	–	29.3/28.4/29.6	63.0/63.4/63.8	80.1/80.2/80.0	27.7/27.6/29.6	69.5/69.2/68.8	69.5/69.3/69.5	69.0/69.3/69.3	81.0/81.0/81.0	73.8/73.6/73.7	77.7/78.2/77.9	64.1/64.0/64.3
SFT on AfriDoc-MT (sentence)												
LLaMAX3-SFT	8B	22.2/22.8/24.1	29.0/25.9/26.8	38.4/39.0/42.2	32.3/32.3/33.8	33.3/29.7/33.7	22.6/21.1/20.2	22.1/20.5/22.9	33.1/26.8/30.2	25.0/23.2/27.2	31.5/27.0/30.9	28.9/26.8/29.2
LLama3.1-SFT	8B	25.2/22.7/25.2	31.8/29.2/31.9	48.5/50.2/48.5	33.8/32.6/33.0	35.4/35.1/38.6	15.6/22.9/24.2	20.6/18.6/24.1	28.7/31.3/33.7	25.6/23.5/30.2	24.2/25.2/29.3	28.9/29.1/31.9
SFT on AfriDoc-MT (pseudo-document with 10)												
LLaMAX3-SFT	8B	37.8/35.9/37.1	49.7/48.2/51.9	72.4/70.5/74.4	50.7/50.1/52.2	55.0/53.4/52.4	64.0/62.7/62.5	66.7/63.5/66.3	75.4/74.4/77.8	71.8/68.3/71.8	74.1/73.8/74.0	61.7/60.1/62.0
LLama3.1-SFT	8B	26.7/27.6/27.4	46.0/49.7/49.6	64.1/64.0/63.4	50.3/50.0/49.5	44.5/44.6/47.0	57.8/56.5/63.8	61.7/55.3/59.6	47.3/53.1/74.4	55.6/61.0/68.9	68.2/59.9/71.4	52.2/52.2/57.5

Table 17: Performance results of various models on the pseudo-document-level task for the Health domain, measured using document level metric d-BLEU and d-CHRF.

Model	Size	*eng → X*					*X → eng*					AVG
		amh	hau	swa	yor	zul	amh	hau	swa	yor	zul	
						BLEU						
Encoder-Decoder												
Toucan	1.2B	2.2	11.2	13.2	4.1	7.4	8.6	15.6	17.9	10.4	14.8	10.5
NLLB-200	1.3B	5.1	11.2	14.0	2.7	9.8	5.8	9.7	21.9	8.1	16.9	10.5
NLLB-200	3.3B	5.1	7.2	11.9	2.2	7.4	10.7	12.9	26.5	10.3	20.9	11.5
MADLAD-400	3B	5.7	6.8	5.4	1.2	6.7	30.6	33.6	39.4	14.9	35.5	18.0
MADLAD-400	7.2B	1.2	4.7	5.0	1.5	4.3	21.2	17.9	31.6	6.7	20.3	11.4
Aya-101	13B	6.3/6.7/5.7	19.5/20.2/18.2	19.5/14.4/5.5	4.1/4.5/4.4	13.0/13.4/11.8	29.0/29.9/7.2	35.5/35.6/24.0	39.8/39.8/25.6	25.1/25.5/22.6	40.0/40.4/36.6	23.2/23.0/16.2
SFT on AfriDoc-MT (sentence)												
NLLB-SFT	1.3B	7.8	17.1	24.3	7.4	15.3	11.7	19.5	25.5	13.6	23.4	16.6
SFT on AfriDoc-MT (pseudo-document with 10)												
NLLB	1.3B	8.6	17.4	24.2	7.4	15.2	22.3	23.9	28.9	17.4	27.4	19.3
Decoder-only												
Gemma2-IT	9B	0.2/0.2/0.2	11.4/11.6/8.7	18.8/21.0/14.3	0.3/0.3/0.3	0.7/0.7/0.8	8.5/9.0/8.3	22.1/22.9/21.6	30.3/32.3/28.6	15.1/16.7/12.1	21.6/24.4/19.3	12.9/13.9/11.4
LLama3.1-IT	8B	0.2/0.1/0.1	0.8/0.7/0.6	9.6/8.8/9.5	0.2/0.2/0.2	0.2/0.1/0.1	4.9/5.1/4.5	19.4/19.7/2.2	30.8/31.1/1.6	8.9/10.2/4.5	8.7/8.8/6.0	8.4/8.5/2.9
LLaMAX3-Alp	8B	0.5/0.5/0.5	3.7/3.2/4.7	4.8/5.6/3.2	0.6/0.6/0.7	1.6/1.4/1.8	4.8/5.3/6.7	22.4/23.7/18.8	30.9/24.1/33.5	2.3/2.9/2.2	19.8/21.7/20.3	9.1/8.9/9.2
GPT-3.5	–	0.4/0.4/0.5	2.3/2.4/2.6	35.8/34.8/35.8	0.6/0.6/0.6	2.8/3.0/2.8	3.6/4.5/3.8	19.8/20.1/18.9	45.5/45.6/45.3	15.7/16.0/16.4	25.7/27.1/27.1	15.2/15.4/15.4
GPT-4o	–	5.9/6.1/6.1	28.8/29.0/28.8	40.8/41.2/41.0	7.0/7.4/7.4	26.2/26.1/25.8	35.0/35.4/35.1	42.8/43.3/43.0	51.1/51.2/51.0	38.6/39.3/38.7	51.6/51.6/51.7	32.8/33.1/32.9
SFT on AfriDoc-MT (sentence)												
LLaMAX3-SFT	8B	2.7/2.9/2.6	2.8/2.5/3.0	5.2/5.1/4.8	4.2/4.2/4.3	2.5/2.5/2.7	4.8/4.9/4.9	2.6/3.9/3.9	4.9/6.0/5.1	3.3/4.7/4.7	5.0/5.5/4.4	3.8/4.2/4.0
LLama3.1-SFT	8B	1.8/1.9/2.0	3.0/3.1/3.1	5.9/6.0/6.8	5.0/4.9/5.1	2.1/2.3/2.3	2.2/2.1/3.2	3.8/3.9/4.4	6.2/4.7/7.3	5.0/4.4/6.2	4.8/3.6/6.0	4.0/3.7/4.6
SFT on AfriDoc-MT (pseudo-document with 10)												
LLaMAX3-SFT	8B	7.8/8.8/9.8	14.0/15.5/17.8	22.6/24.0/27.7	13.0/14.7/15.0	12.7/10.8/13.7	32.5/30.0/32.1	37.6/33.7/38.2	43.0/40.2/45.2	36.5/31.4/36.8	43.2/36.9/43.5	26.3/24.6/28.0
LLama3.1-SFT	8B	2.8/3.0/3.0	9.6/9.1/8.0	15.9/14.3/11.3	17.6/14.8/16.1	5.9/5.1/5.5	25.0/19.9/26.0	22.8/22.5/33.6	11.6/23.3/42.0	14.6/25.8/34.9	34.4/30.2/34.0	16.0/16.8/21.4
						CHRF						
Encoder-Decoder												
Toucan	1.2B	18.8	41.8	42.5	22.9	39.2	39.0	44.3	46.8	41.1	44.3	38.1
NLLB-200	1.3B	26.7	40.4	42.8	18.8	40.6	30.1	35.0	49.6	32.9	43.2	36.0
NLLB-200	3.3B	26.4	33.4	39.3	17.4	35.0	36.7	38.9	54.4	36.4	47.6	36.5
MADLAD-400	3B	29.5	38.3	31.7	15.1	44.1	62.6	63.5	66.4	45.9	63.4	46.0
MADLAD-400	7.2B	5.2	30.8	33.1	14.2	27.7	46.3	40.8	56.0	23.7	44.0	32.2
Aya-101	13B	29.1/30.1/26.1	54.0/55.0/51.2	51.7/45.3/30.5	21.5/22.3/21.8	53.3/55.0/51.2	61.4/62.5/16.7	65.3/65.5/50.9	68.8/68.7/51.7	55.6/55.7/51.5	68.1/68.4/64.7	52.9/52.9/41.6
SFT on AfriDoc-MT (sentence)												
NLLB-SFT	1.3B	31.4	47.9	54.7	30.2	49.8	38.8	47.0	53.0	41.3	50.8	44.5
SFT on AfriDoc-MT (pseudo-document with 10)												
NLLB	1.3B	32.8	48.0	54.6	29.6	49.9	52.4	52.4	56.3	47.1	54.8	47.8
Decoder-only												
Gemma2-IT	9B	5.7/6.2/5.7	39.9/42.1/34.5	46.7/51.0/38.7	6.6/6.6/6.4	14.9/14.8/15.4	34.7/35.9/34.0	49.4/50.1/48.2	55.4/57.7/53.6	45.7/48.2/40.7	48.4/51.7/45.8	34.7/36.4/32.3
LLama3.1-IT	8B	7.4/7.2/6.8	15.3/13.9/14.1	42.0/43.3/32.4	6.1/5.7/6.2	8.8/8.2/8.8	25.6/26.1/23.0	48.3/48.7/17.4	58.7/59.0/16.0	31.0/34.4/23.4	32.0/34.7/27.8	27.5/28.1/17.6
LLaMAX3-Alp	8B	10.9/10.8/11.4	30.5/27.8/32.5	35.5/38.1/29.0	11.2/11.5/12.0	26.1/24.1/26.0	28.5/29.4/29.0	50.4/51.4/48.5	58.5/54.3/62.4	22.5/24.7/21.8	48.7/48.3/48.8	32.3/32.0/32.1
GPT-3.5	–	13.2/13.4/13.5	28.7/28.7/29.7	72.1/71.7/72.0	12.4/12.2/12.7	33.8/35.1/33.8	36.8/38.5/38.5	56.2/56.3/54.5	73.4/73.5/73.2	51.5/52.7/53.0	58.8/61.2/60.9	43.7/44.3/44.2
GPT-4o	–	31.1/30.4/31.3	64.7/65.1/64.6	75.1/75.0/75.0	27.8/28.0/28.1	70.7/70.6/70.7	68.4/68.6/68.2	71.4/71.6/71.2	76.4/76.5/76.3	69.9/70.1/69.8	76.5/76.5/76.3	63.2/63.2/63.2
SFT on AfriDoc-MT (sentence)												
LLaMAX3-SFT	8B	21.3/21.5/21.7	29.1/27.9/29.9	36.3/37.0/34.7	30.2/30.1/30.5	31.3/31.4/31.7	21.4/24.2/21.2	22.0/27.6/26.0	29.5/32.3/30.0	23.6/28.5/26.2	29.7/29.8/27.1	27.4/29.0/27.9
LLama3.1-SFT	8B	20.4/20.9/21.0	30.6/30.8/30.0	38.3/38.5/40.0	32.8/32.3/33.4	26.3/29.3/28.2	12.2/22.0/23.9	27.2/28.6/28.9	33.5/28.7/36.9	29.1/29.7/32.2	29.5/26.2/32.3	28.0/28.7/30.7
SFT on AfriDoc-MT (pseudo-document with 10)												
LLaMAX3-SFT	8B	34.7/36.4/37.7	54.1/58.1/58.6	64.7/62.9/68.3	47.2/47.9/49.3	58.9/56.5/60.9	65.4/63.5/64.2	68.2/66.3/68.5	70.7/70.8/73.1	67.5/66.2/67.7	71.4/69.3/71.6	60.3/59.8/62.0
LLama3.1-SFT	8B	22.6/23.5/23.7	47.0/45.2/46.7	58.6/57.2/51.4	49.7/47.2/49.5	43.8/40.0/41.4	59.9/55.8/60.9	58.0/56.1/65.4	35.8/51.3/71.1	44.1/57.2/66.3	66.1/60.1/66.4	48.6/49.4/54.3

Table 18: Performance results of various models on the pseudo-document-level task for the Tech domain, measured using document level metric d-BLEU and d-CHRF.

Prompt 1

```
{system_prompt}
Translate the following {source_language} text to {target_language}:
Provide only the translation.
{source_language} text: {{source_sentence}}
{target_sentence} text:
```

Prompt 2

```
{system_prompt}
Translate the following {domain} text from {source_language} to {target_language}:
Provide only the translation.
{source_language} document: {{source_document}}
{target_language} document:
```

Prompt 3

```
{system_prompt}
Please provide the {target_language} translation for the following {source_language} text:{{source_document}}
Provide only the translation.
```

Prompt 1

```
{system_prompt}
Translate the following {source_language} document to {target_language}:
Provide only the translation.
{source_language} document: {{source_document}}
{target_language} document:
```

Prompt 2

```
{system_prompt}
Translate the following {domain} document from {source_language} to {target_language}:
Provide only the translation.
{source_language} document: {{source_document}}
{target_language} document:
```

Prompt 3

```
{system_prompt}
Please provide the {target_language} translation for the following {source_language} document:{{source_document}}
Provide only the translation.
```

Table 19: The task prompts used for evaluating LLMs are applied to both sentence-level and document-level translation tasks.

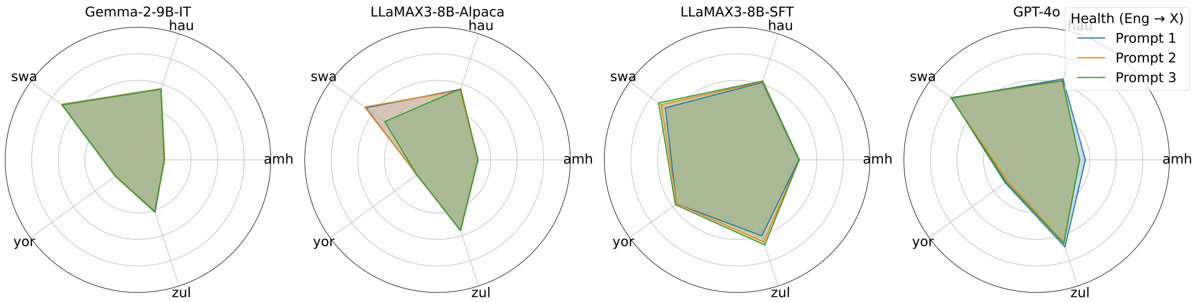

Figure 16: d-CHRF scores for some LLMs for sentence-level translation using different prompts when translating into African languages

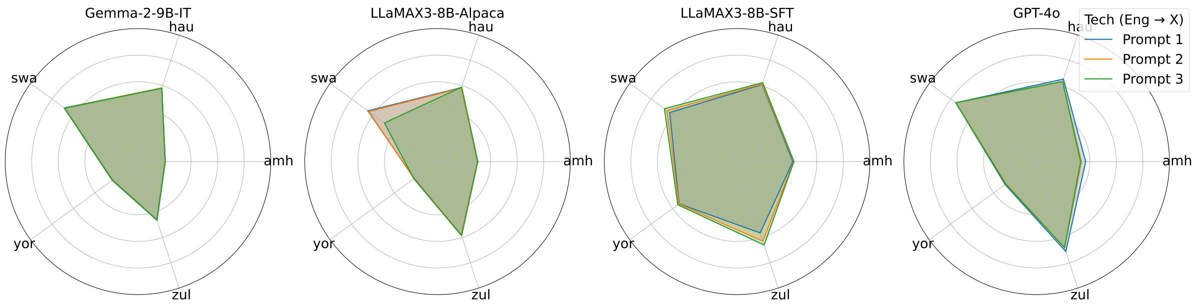

Figure 17: d-CHRF scores for some LLMs for sentence-level translation using different prompts when translating into African languages

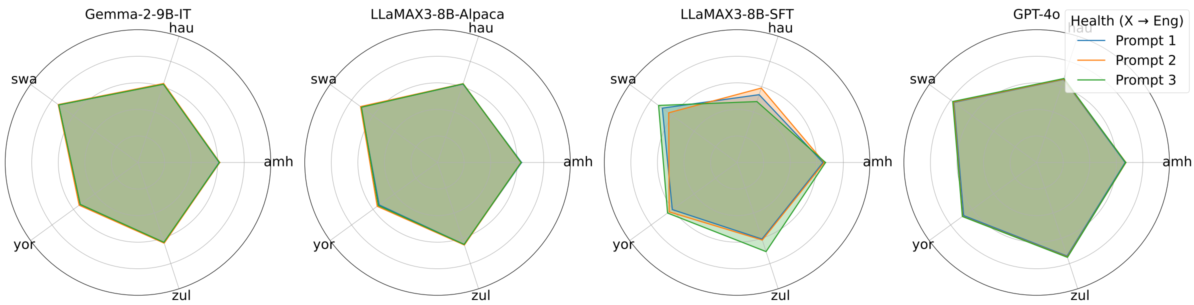

Figure 18: d-CHRF scores for some LLMs for sentence-level translation using different prompts when translating into English

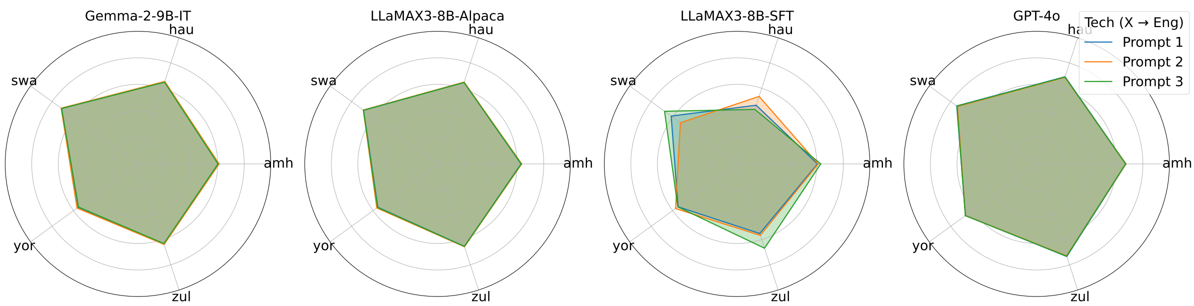

Figure 19: d-CHRF scores for some LLMs for sentence-level translation using different prompts when translating into English

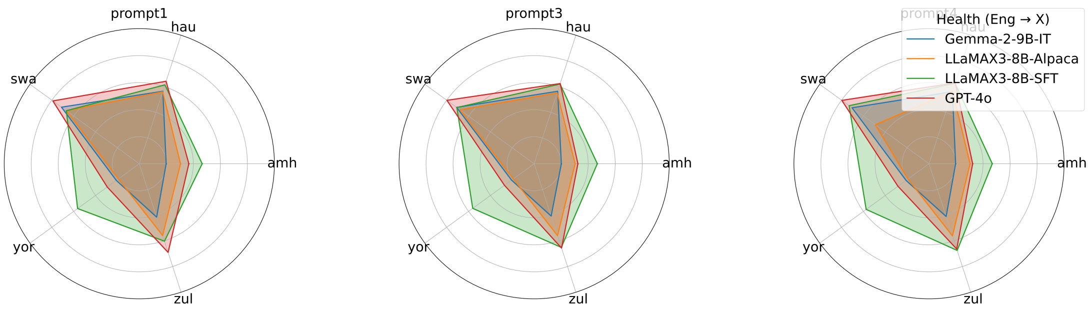

Figure 20: dCHRF scores for some LLMs for sentence-level translation using different prompts when translating into African languages

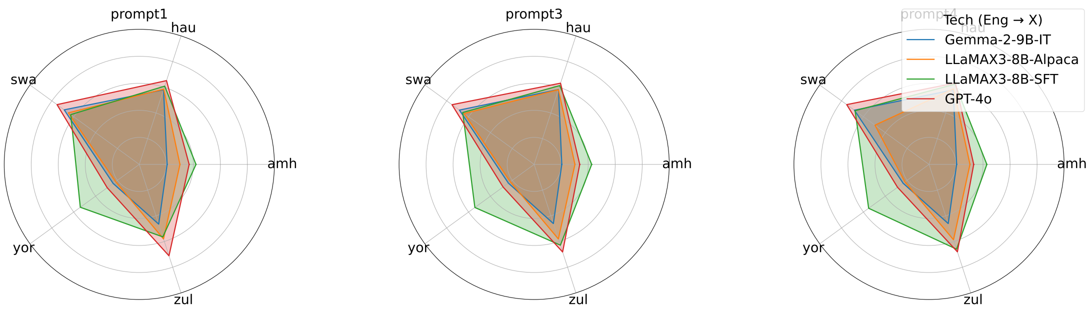

Figure 21: d-CHRF scores for some LLMs for sentence-level translation using different prompts when translating into African languages

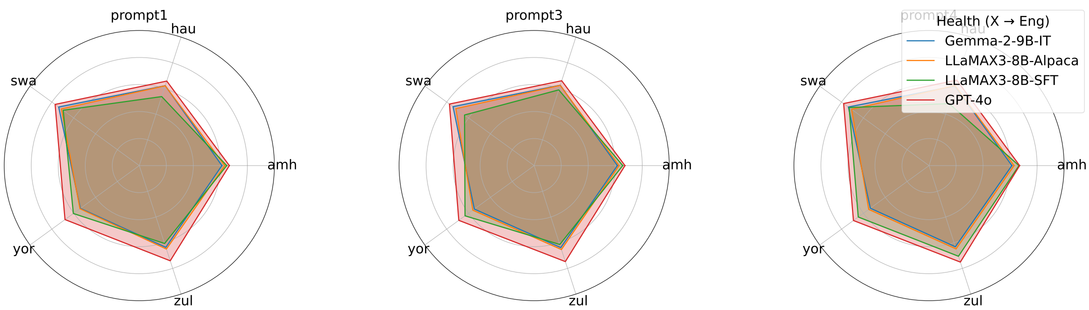

Figure 22: d-CHRF scores for some LLMs for sentence-level translation using different prompts when translating into English

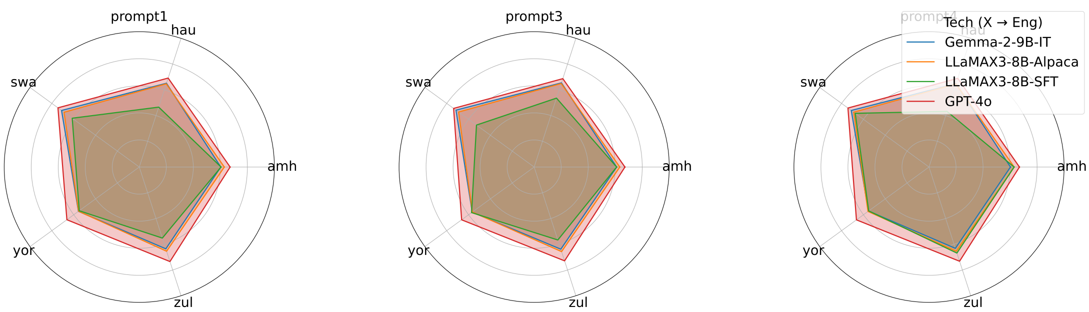

Figure 23: d-CHRF scores for some LLMs for sentence-level translation using different prompts when translating into English