🦁 Where Are We?
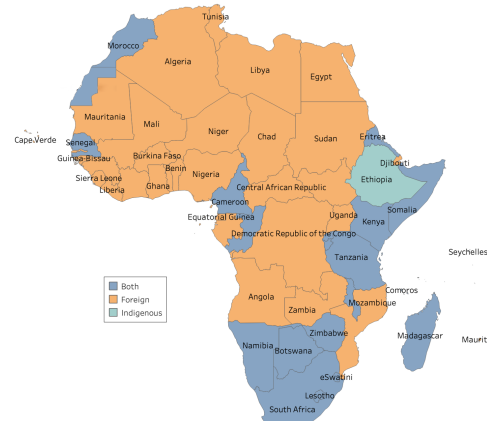# Evaluating LLM Performance on African Languages

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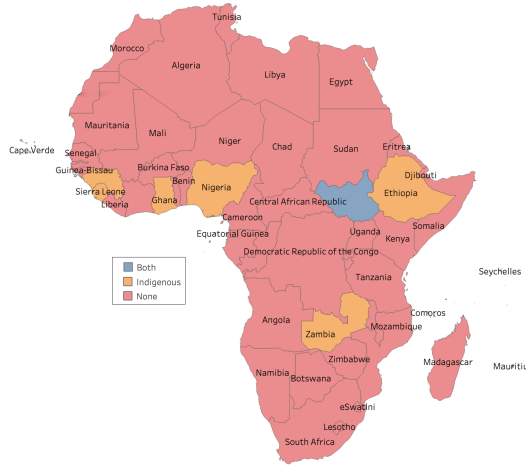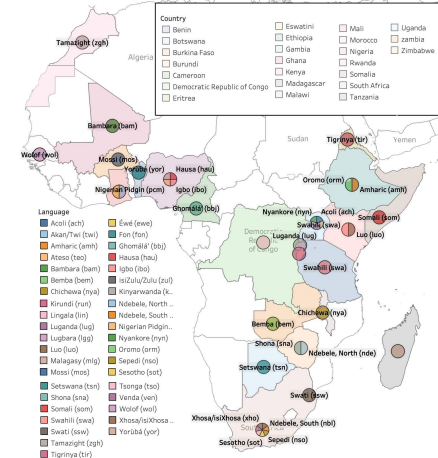[ξ]The University of British Columbia   [Ω]MBZUAI   [λ]Invertible AI

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(a) Language policies for education across Africa.

(b) Official national language policies across Africa.

(c) Official regional language policies across Africa. *None* means no additional policy is available on a regional level.

(d) We collect SAHARA to empirically evaluate LLM performance on African languages, allowing us to demonstrate with evidence how current language policies directly impact progress in the field.

Figure 1: Maps of Africa showing the languages covered in this work and the language policies across the continent. The term *Indigenous* language is broadly defined here as one that is 'native' to the area (Walsh, 2005). The term *Both* in maps (a), (b), and (c) refers to *Indigenous* and *foreign* languages combined. Knowledge of what is an Indigenous language is based exclusively on *Ethnologue* (https://www.ethnologue.com).

Abstract

Africa's rich linguistic heritage remains underrepresented in NLP, largely due to historical policies that favor foreign languages and create significant data inequities. In this paper, we integrate theoretical insights on Africa's language landscape with an empirical evaluation using SAHARA— a comprehensive benchmark we curate from large-scale, publicly accessible datasets capturing the continent's linguistic diversity. By systematically assessing the performance of leading large language mod-

els (LLMs) on SAHARA, we demonstrate how policy-induced data variations directly impact model effectiveness across African languages.[1] Our findings reveal that while models perform reasonably well on few languages, many Indigenous languages remain marginalized due to sparse data. Leveraging these insights, we offer actionable recommendations for policy reforms and inclusive data practices. Overall, our work underscores the urgent need for a dual approach—combining theoretical understanding with empirical evaluation—to foster linguistic diversity in AI for African communities.

1 Introduction

The digital landscape of Africa is as diverse as its cultures and languages, yet the continent's rich linguistic heritage remains largely underrepresented in NLP research. Despite significant transformations over the past decade driven by advances in large language models (LLMs) and a growing interest in linguistic diversity, most efforts have concentrated on a handful of widely spoken languages such as Swahili, Afrikaans, and Hausa, while many Indigenous languages continue to be sidelined due to the paucity of accessible, high-quality datasets. This oversight, deeply rooted in historical language policies that have neglected robust data collection and accessibility, has far-reaching implications for the development of language technology across Africa (Eberhard et al., 2021). Recent initiatives, including the work of Masakhane (Dione et al., 2023b; Adelani et al., 2021c, 2023, 2024b; Bandarkar et al., 2024a) and the efforts of platforms like HuggingFace, have begun to address these challenges by curating language-specific datasets and adapting transfer learning techniques for low-resource African languages. Models such as Cheetah (Adebara et al., 2024a), Serengeti (Adebara et al., 2023), Toucan (Elmadany et al., 2024), Afri-XLMR (Alabi et al., 2022), AfriTeVa (Oladipo et al., 2023; Jude Ogundepo et al., 2022), mBERT (Devlin et al., 2018), XLM-R (Conneau et al., 2020), and LLaMA (Touvron et al., 2023) have leveraged multilingual data to enhance performance on these languages, yet progress remains uneven—highlighting that the advancements achieved are primarily concentrated on a select few.

In this study, we undertake a comprehensive empirical evaluation of leading LLMs on an extensive benchmark that we collect using mostly existing datasets to unravel how current African language policies, by dictating data availability and accessibility, directly shape model performance across the continent's diverse linguistic spectrum. By systematically analyzing the distribution of existing datasets across languages and performance patterns among various LLMs, we not only pinpoint which languages benefit from ample data resources but also illuminate the underlying factors that contribute to their relative success. Our investigation reveals that the disparities in NLP outcomes are closely tied to policy-driven data inequities, offering concrete evidence of the need for more inclusive, forward-thinking language policies. These insights provide actionable recommendations for enhancing dataset creation and model training, ultimately aiming to bridge the digital divide and foster linguistic diversity in artificial intelligence for African communities.

Overall, we make the following contributions: **(1) Benchmark with wide, diverse coverage.** We introduce *Sahara*, a comprehensive benchmark assembled from large-scale, publicly accessible, and inclusive datasets that capture the rich linguistic diversity of Africa. This benchmark enables a systematic evaluation of data availability and model performance across a broad range of African languages. **(2) Dynamic leaderboard.** We develop a dynamic leaderboard built on best design practices, providing a transparent and continually updated platform to track progress and benchmark innovations in African NLP. **(3) Empirical evaluation.** We perform an extensive empirical assessment of a wide spectrum of models thereby establishing robust baselines and revealing performance disparities linked to data resource availability. **(4) Policy-driven and actionable insights.** We uncover clear links between current language policies, data availability, and model performance, demonstrating how policy-induced data inequities shape the effectiveness of language models across Africa. Our analysis provides recommendations for future research and development by informing policy reforms that foster more inclusive language technologies tailored to the needs of African communities. We now discuss language polices in Africa.

2 Language Policies in Africa

Across Africa, the predominant response to the continent's multilingual landscape has been the

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adoption of a foreign language for official functions. However, in some instances, select Indigenous African languages receive official recognition at regional or national levels or within educational contexts (Petzell, 2012; Foster, 2021; Ouane and Glanz, 2010). [2] For instance in Nigeria, English is the official language, with only three out of 512 Indigenous languages recognized at the regional level. Similarly, Ghana designates English as its official language while also recognizing ten of its 73 Indigenous languages for institutional use. In Tanzania, Swahili is the sole Indigenous official language among 118 languages, alongside English. Kenya grants official status to 12 of its 61 languages, while South Africa recognizes 12 out of 20 Indigenous languages as institutional languages (Adebara and Abdul-Mageed, 2022). Figures 1(a), 1(b), 1(c), and 1(d) illustrate the distribution of language policies across the continent.

Even when Indigenous languages are granted official status alongside foreign languages, they often serve a symbolic rather than functional role. For instance, although Kiswahili is recognized as an official language by the African Union, its website and official document releases remain in English and French. A similar pattern emerges in education systems: where Indigenous languages are used, their role is typically confined to early childhood education and is usually paired with a foreign language rather than serving as the sole medium of instruction (Petzell, 2012; Foster, 2021; Ouane and Glanz, 2010). These language policies significantly shape language use across various domains, including newspapers, radio, television, and social media. Due to the dominance of foreign languages in official contexts, major newspapers and government publications are predominantly produced in languages such as English, French, and Portuguese, thereby limiting access for speakers of Indigenous languages (ResCue and Agbozo, 2021). Although some Indigenous languages are used on television and radio, foreign languages tend to dominate national broadcasts, especially in political discourse

and formal news reporting (Cheo et al., 2023; Myers and Harford, 2020; National Communications Authority, 2016).

Social media presents a more flexible environment where users can communicate in Indigenous languages; however, platform support remains uneven (Sunday et al., 2018; Molale and Mpofu, 2023; ResCue and Agbozo, 2021). Many African languages are underrepresented in digital spaces, lacking features such as text input options, spell checkers, or automated translation services. Consequently, users often resort to code-switching between Indigenous and dominant foreign languages, reinforcing existing linguistic divides. These trends underscore how official language policies shape broader language use, ultimately contributing to the marginalization of Indigenous languages in both public and digital communication spheres.

The analysis of language policies in Africa reveals how historical choices have led to significant data imbalances for Indigenous languages. Motivated by this, we built our benchmark, SA-HARA to evaluate how these policies directly impact data availability, coverage, and the performance of LLMs on African languages. In the following section, we detail the construction of SA-HARA and demonstrate its role in linking language policy to empirical outcomes in NLP.

3 Related Work

The development of NLP for African languages is hindered by data scarcity, policy-induced disparities, and suboptimal model performance. Recent initiatives have sought to mitigate these challenges by curating diverse datasets, rigorously evaluating multilingual models, and advocating for more inclusive language policies. For example, several initiatives have contributed to expanding datasets for African (Yimam et al., 2020; Muhammad et al., 2022; Aliyu et al., 2022; Muhammad et al., 2023b,a; Ilevbare et al., 2024; Elmadany et al., 2024). Some notable ones like Adelani et al. (2021c, 2022b) introduced MasakhaNER, a named entity recognition dataset for 10 African languages, highlighting the limitations in existing resources. Similarly, IROKOBench (Adelani et al., 2024b) evaluated LLMs on African languages, revealing stark performance gaps between high- and low-resource languages. Adebara et al. (2022) developed AfroLID, a neural language identification model covering 517 African languages, showing

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[2]An *Indigenous* language is defined here as one that is *native* to a particular region, rather than introduced from elsewhere, in contrast to a *foreign* language, which may nonetheless serve as the mother tongue for certain local populations (Walsh, 2005). A *national* language refers to a language spoken broadly across an entire country. A *regional* language is spoken by a significant number of people within a specific area but does not have widespread national usage. An *educational* language is officially designated as a medium of instruction within the educational system.

that most languages lack NLP datasets beyond language identification.

Language policies play a crucial role in determining resource availability. Adebara and Abdul-Mageed (2022); Hershcovich et al. (2022) emphasized the sociolinguistic factors affecting NLP development, noting that languages with official status receive more institutional support, fostering greater digital representation. Bird (2020) further critiqued the Western-centric approach in speech and language technologies, calling for AI models that align with Indigenous linguistic contexts. Model performance in African languages remains uneven, largely due to the dominance of high-resource languages in multilingual training. Conneau et al. (2018) introduced XLM-R, demonstrating the limitations of cross-lingual transfer learning for underrepresented languages. Meta AI's No Language Left Behind (NLLB) project (Costa-jussà et al., 2022) attempted to improve multilingual models for low-resource languages, but performance remained inconsistent, particularly in generation tasks. Despite these advances, African NLP still requires increased investment in dataset curation, inclusive policy frameworks, and model development tailored to the linguistic diversity of the continent. We now introduce SAHARA.

4 🦫 Sahara Benchmark

Our objective is to create a comprehensive benchmark for African NLP that enables (i) analysis of existing language resources and (ii) the assessment of language models and tracking of the progress of African NLP. To achieve this goal, we develop SAHARA, adhering to several key design principles that we will now elucidate. SAHARA establishes a comprehensive and adaptable benchmark for African NLP using publicly available datasets. Figure shows coverage of SAHARA.

Wide and Diverse Coverage. SAHARA is the most comprehensive benchmark for African NLP, covering a vast range of languages. We achieve this by collecting high-quality, publicly available datasets from as many African languages as possible, ensuring easy accessibility for researchers evaluating their models. As a result, SAHARA supports 517 languages across various tasks, making it the most extensive and representative benchmark for African NLP. It encompasses languages from 50 out of 54 African countries and includes data

written in five different scripts: *Arabic, Coptic, Ethiopic, Latin*, and *Vai*, spanning five language families across the continent.

Tasks and Task Clusters. SAHARA is designed to support a broad spectrum of NLP tasks, which we systematically organize into coherent task clusters. The inclusion of well-defined, challenging clusters enables a more meaningful assessment of a model's capabilities and allows researchers to evaluate performance on specific clusters. As shown in Table 1, SAHARA comprises four clusters: *text classification*, *text generation*, *multiple-choice, comprehensive and reasoning (MCCR)*, and *token-level classification*. For further details on the datasets used for each task, please refer to Appendix A.

Modular Public Leaderboard. We implement a *user-friendly leaderboard* for model evaluation on SAHARA, hosted on Hugging Face (HF) Spaces. Evaluated models must be publicly available in HF repositories to ensure seamless integration. When submitting a model, users are required to provide detailed *metadata*—including whether the model is pretrained, further pretrained, or instructed—and then submit an evaluation request. The submission enters a processing queue, and once evaluation is complete, the results are automatically displayed on the leaderboard. Our team will actively maintain the leaderboard by continuously integrating new publicly available tasks and datasets to keep it *up-to-date*. SAHARA thus serves as a valuable tool for assessing model performance in African NLP, accelerating the development of high-performance models, and contributing to the field's growth. In addition to evaluating models on the entire benchmark, users have the flexibility to assess performance on specific task clusters, encouraging the development of specialized models tailored to address the unique challenges of African NLP.

5 Experiments and Results

5.1 Experimental Setup

To comprehensively assess the progress of African NLP, we systematically evaluate a range of widely used instruction-based LLMs in a few-shot setting on the SAHARA benchmark. We include both open and closed LLMs, such as Phi-3.5 and Phi-4 (Abdin et al., 2024), Gemma family (Team et al., 2024) models including Gemma-2 (2, 9, 27B) and Gemma-3 (4, 12, 27B), Llama family models (Dubey et al., 2024) including Llama-3.1 (8,

Cluster	Task	Identifier	#AL	#DS
Classification	Cross-Lingual Natural Language Inference (Adelani et al., 2024b)	xnli	16	1
	Language Identification (Adebara et al., 2022)	langid	517	1
	News Classification (Azime and Mohammed, 2021; Niyongabo et al., 2020; David, 2020a)	news	4	3
	Sentiment Analysis (Diallo et al., 2021; Oyewusi et al., 2020; Shode et al., 2022a)	sentiment	3	3
	Topic Classification (Hedderich et al., 2020)	topic	2	1
Generation	Machine Translation (Adelani et al., 2022a; Reid et al., 2021a; Ogueji and Ahia, 2019; Akera et al., 2022)	mt	29	5
	Paraphrase (Scherrer, 2020)	paraphrase	4	1
	Summarization (Hasan et al., 2021; Adebara et al., 2024b)	summary	10	2
	Title Generation (Hasan et al., 2021; Adebara et al., 2024b)	title-gen	10	2
MCCR	General Knowledge (Adelani et al., 2024b)	mmlu	16	1
	Mathematical Word Problems (Adelani et al., 2024b)	mgsm	16	1
	Reading Comprehension (Bandarkar et al., 2024a)	reading-comp	25	1
	Context-based Question Answering (Clark et al., 2020)	squad-qa	1	1
Tokens	NER (Adelani et al., 2021a, 2022c; Eiselen, 2016; Alabi et al., 2020a; Pan et al., 2017)	ner	27	5
	Phrase Chunking (Eiselen, 2016)	chunking	8	1
	POS Tagging (Onyenwe et al., 2018a, 2019)	pos	1	1
Total	**16**		**517**	**30**

Table 1: Descriptive statistics of languages and dataset diversity in SAHARA across different tasks and task-clusters. **#AL:** African Languages, **#DS:** datasets, **MCCR:** multiple-choice, comprehensive and reasoning task-cluster.

70B), Llama-3.2 (1, 3B), and Llama-3.3 (70B), Aya models (8, 23B) (Aryabumi et al., 2024), and Command family models (Cohere et al., 2025) including Command-R-Plus-R7B, Command-R-Plus (104B) and Command-A (111B), as well as proprietary models such as GPT-4.1[3] (Achiam et al., 2023) and Claude-4-Sonnet[4] (Anthropic, 2024). We further analyze performance by categorizing models according to *size*: small language models (SLM, <8B parameters) and large language models (LLM, ≥8B parameters), allowing investigation of the relationship between scale and effectiveness. For robust comparison, we aggregate evaluation datasets according to task clusters described in Appendix A. From each task, we randomly sample 1,000 data points for few-shot testing, employing well-curated, concise prompts—examples of which appear in Appendix C1.

5.2 Results and Discussion

We evaluate 24 LMs across four task clusters, maintaining a consistent assessment approach while varying evaluation metrics. Depending on the task, we employ *Exact Match*, F_1, *Accuracy*, *spBLEU^{1K}* (Elmadany et al., 2024), and *RougeL* scores.

As shown in Table 2, in the *classification tasks*, the closed models Claude-4-Sonnet and GPT-4.1 consistently lead in performance, followed by larger LLMs such as Gemma3 (27B) and CommandR-Plus-104B. In the *language identification task*, most models struggle to grasp the task effectively, with only the larger LLMs demonstrat-

ing some understanding, suggesting that model size is crucial for achieving higher accuracy across various multilingual tasks. In the *generation task cluster*, larger models perform as expected, with GPT-4.1 and Llama-3.1 (70B) achieving the best results. There is a noticeable performance increase across all models in the paraphrase task, while the summarization task exhibits a more balanced performance among all models. Considering their size, Phi-3.5 and Gemma3 (4B) perform well within this task cluster. In the *MCCR tasks*, Command-A (111B) performs competitively against the closed Claude-4-Sonnet model. In the MGSM task, which involves solving mathematical word problems, most open-source models perform poorly, while Claude-4-Sonnet excels, achieving an exact match score of 22.34%. In token-level tasks, GPT-4.1 and Command-A (111B) consistently deliver strong performances, whereas the Aya model family struggle to grasp the tasks.

Results demonstrate a nuanced landscape of performance across multilingual and African LLMs, with notable variations depending on parameter size and task type. In few-shot settings, the closed model Claude-4-Sonnet achieves the highest overall average score (40.82), outperforming all open models across most task clusters. Among open models, Command-A (111B) and Gemma-3 (27B) also exhibit strong performance, particularly in downstream tasks such as reasoning tasks, where Gemma2 (27B) reaches top score of 82.49 on Squad-QA and Command-A achieves 61.91 on MMLU task. For smaller parameter regimes, Gemma-2 (2B) and Phi-4 (3.8B) demonstrate the best performance on their model size. Furthermore,

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[3]**GPT-41.1 version:** gpt-4.1-2025-04-14.

[4]**Claude-4-Sonnet version:** claude-4-sonnet-20250514

Cluster	Identifier	Metric	Shots	SLM S1	S2	S3	S4	S5	S6	LLM L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14	L15	L16	Closed LLM CL1	CL2
Classification xlni	Acc.	5	33.6	33.7	36.7	41.18	40.4	46.68	48.08	55.06	34.3	40.69	37.09	61.09	57.86	65.58	44.2	38.19	51.89	48.38	52.09	35.87	46.77	59.67	69	69.6
lid	F_1	10	0	0	0.87	0.26	0.85	0.77	2.82	3.6	0	1.49	2.27	1.95	4.61	4	1.81	3.34	3.26	3.07	3.3	3.05	3.32	4.57	3.73	4.48
news	F_1	3	0.86	0.35	0.15	17.54	0	6.64	21.94	0	2.06	24.06	0.12	25.83	7.83	35.56	28.03	0.61	35.26	33.31	34.81	3.45	30.46	28.66	40.09	32.19
sentiment	F_1	5	38.51	24.75	30.45	11.05	28.77	1.99	36.09	42.47	38.4	28.36	36.07	34.56	20.55	46.35	35.86	25.94	24.51	45.82	35.89	19.98	37.07	47.14	55.67	57.52
topic	F_1	3	8.73	31.62	20.3	19.79	12.46	17.15	48.11	39.35	34.95	28.55	42.12	44.3	31.8	70.73	36.47	43.74	64.89	56.48	48.73	52.09	50.96	53.16	67.93	76.57
Avg.			16.34	18.08	17.69	17.96	16.50	14.65	31.41	28.10	21.94	24.63	23.53	33.55	24.53	44.44	29.27	22.36	35.96	37.41	34.96	22.89	33.72	38.64	47.28	48.07
Generation mt_eng2xx	spBleu^{1K}	5	1.79	3.63	3.45	3.25	2.12	3.4	7.07	7.61	1.72	4.37	2.79	6.24	6.91	4.56	3.73	3.29	8.84	8.7	9.36	1.4	6.06	8.22	12.18	12.36
mt_fra2xx	spBleu^{1K}	5	0.79	0.36	0.74	1.05	1.25	1.32	0.73	0.95	0.7	1.19	0.66	2.03	1.67	2.05	1.15	0.82	1.93	1.87	1.77	1.05	1.04	2.3	3.41	3.42
mt_xx2xx	spBleu^{1K}	5	0.4	0.45	0.42	0.42	0.36	0.18	0.43	0.63	0.72	0.55	0.46	0.71	0.9	1.39	0.55	0.17	1.28	1.05	1.37	0.67	0.38	0.85	5.15	4.44
paraphrase	spBleu^{1K}	5	23.2	28.88	31.15	19.12	25.93	17.85	28.73	25.83	31.68	31.33	23.66	17.26	21.34	15.37	32.13	30.68	26.86	19.64	27.79	19.23	36.06	26.06	23.2	20.35
summary	rougeL	2	10.03	3.24	4.37	10.07	0.91	13.34	15.1	10.43	1.45	12.74	5.92	16.16	15.73	17.13	13.27	4.19	16.92	17.19	16.4	15.46	14.88	16.09	5.99	16.3
title	spBleu^{1K}	2	2.14	2.81	0.25	2.3	0.03	5.78	7.48	5.78	3	5.94	1.58	7.75	7.51	8.65	6.83	3.2	11.07	10.34	8.78	7.32	6.69	8.65	13.62	9.48
Avg.			6.39	6.56	6.73	6.04	5.10	6.98	9.92	8.54	6.55	9.35	5.85	8.36	9.01	8.19	9.61	7.06	11.15	9.80	10.91	7.52	10.85	10.36	10.59	11.06
MCCR mmlu	Acc.	5	24.09	28.5	28.68	27.29	28.9	30.99	31.88	40.9	26.4	44.51	22.1	42.09	44.9	60.71	51.5	24	56.51	59.3	50.42	59.81	29.8	61.91	81.6	58.6
mgsm	ExactM	5	2.6	3.21	0	1.2	3.39	0.7	2.9	2.8	3.3	2.7	1.5	2.3	5.3	0.6	4.4	3	10.1	7.51	7.6	4.5	4.39	11.1	45.9	29.5
belebele	Acc.	5	27.71	14.71	25.2	29.31	31.31	24.69	22.7	26.93	25.09	28.24	26.33	25.63	31.04	32.34	33.64	26.61	30.4	35.92	33.72	30.83	20.99	29.12	36.6	39.7
squad_qa	F_1	5	57.45	70.89	67.32	43.13	71.31	74.97	78.04	80.91	52.66	59.48	63.41	73.78	82.49	79.16	69.25	64.64	77.65	76.35	66.25	53.92	74.64	80.05	78.02	76.11
Avg.			27.96	29.33	30.30	25.23	33.73	32.84	33.88	37.89	26.86	33.73	28.34	35.95	40.93	43.20	39.70	29.56	43.67	44.77	39.50	37.27	32.46	45.55	60.53	50.98
Tokens ner	F_1	5	0	0.78	1.76	2.99	0.13	3.65	2.26	7.49	2.35	3.96	0.2	6.03	13.14	11.4	8.51	1.52	6.86	10.54	8.64	6.04	4.3	16.88	35.06	27.04
phrase	F_1	5	14.79	28.5	29.44	11.52	24.91	27.73	15.95	29.35	29.42	16.55	30.87	13.59	30.01	23.97	26.34	23.09	25.55	23.13	16.78	25.13	29.44	31.05	36.69	36.45
pos	F_1	5	8.83	6.73	10.56	8.04	10.3	10.46	9.13	13.2	9.81	11.68	12.52	13.86	19	13.99	18.36	11.4	14.13	15.04	11.52	20.76	13.71	27.54	62.84	38.67
Avg.			7.87	12.00	13.92	7.52	11.78	13.95	9.11	16.68	13.86	10.73	14.53	11.16	20.72	16.45	17.74	12.00	15.51	16.24	12.31	17.31	15.82	25.16	44.86	34.05
Overall			14.64	16.49	17.16	14.19	16.78	17.10	21.08	22.80	17.30	19.61	18.06	22.25	23.80	28.07	24.08	17.75	26.57	27.05	24.42	21.25	23.21	29.93	40.82	36.04

Table 2: Few-shot evaluation across different task clusters/tasks. The highest score for each individual task is in **bold green**, while the best average score across each task cluster (and **overall** score, calculated as average of task cluster averages) is in **bold orange**. __Underline__: refers to the best score across the open source/weights LLMs. **Shots**: number of shots. **SLMs:** S1 Llama3.2 (1B), S2 Llama3.2 (3B), S3 Gemma2 (2B), S4 Phi-3.5 (3.8B), S5 Phi-4 (3.8B), and S6 Gemma3 (4B). **LLMs:** L1 Llama3.1 (8B), L2 Gemma2 (9B), L3 Aya (8B), L4 Babel (9B), L5 Command-R-Plus-R7B (8B), L6 Gemma3 (12B), L7 Gemma2 (27B), L8 Gemma3 (27B), L9 DeepSeek-R1-Distill-Qwen (32B), L10 Aya (35B), L11 Llama3.1 (70B), L12 Llama3.3 (70B), L13 DeepSeek-R1-Distill-Qwen (70B), L14 Babel (83B), L15 Command-R-Plus (104B), L16 Command-A (111B). **CLosed LLMs:** CL1 Claude-4-Sonnet, CL2 GPT-4.1. Table E4 is a full-page version of this table.

Gemma2 (9B, 12B) show consistent mid-to-high performance across various clusters, but do not surpass the larger models in aggregate. Importantly, translating *into* English is consistently easier for the models than translating *from* French, likely reflecting disparities in training data distribution and language representation on the target side. These findings highlight not only the dominance of closed LLMs and very large open models in multilingual tasks, but also the critical influence of resource availability and model scale on task-specific outcomes.

Which LM should I use for reasoning tasks? In a limited resource setting, for mathematical QA tasks that fall in the MCCR cluster, Phi-4 ranks top among SLMs for 16 African Languages. In the LLMs category, Command-A (111B) has better performance on a higher number of African languages. For reading comprehension tasks (belebele), Phi-4 is most suitable in constrained compute resource settings while in scenarios without limits in compute resources, Llama 3.3-70B gives better performance.

Which African language(s) do LMs perform best on? The models achieve their highest performance on a small set of well-resourced African languages—chiefly Hausa, Swahili, Yorùbá, and Afrikaans—across diverse NLP tasks. Both open-source models like Command-A (111B) and Aya-35B and proprietary models such as Claude-4-Sonnet consistently excel on these languages, reflecting their ample labeled and parallel data. This trend spans simple classification and NER tasks to complex reasoning benchmarks (e.g., MMLU, XLNI) and machine translation, underscoring that data availability, rather than linguistic typology, is the primary driver of model effectiveness.

Models explicitly designed with African linguistic diversity, such as Aya-35B, also achieve strong results on Southern Sotho and Lingala—languages that have benefited from recent, community-led data initiatives. Swahili, in particular, ranks among the top languages for Llama3 models, likely due to its standardized orthography, regular morphology, and extensive bilingual corpora. Afrikaans and Swahili similarly perform well within Gemma2 and Command-R-Plus (104B), supported by their inclusion in massive multilingual datasets (e.g., mC4, OSCAR, WMT) and, in Afrikaans's case, established government-supported digital media.

Overall, our findings reveal that LM performance correlates strongly with the volume and diversity of available data. Underperformance on

low-resource African languages is not a function of inherent complexity but of underrepresentation in training data. Bridging this gap will require concerted efforts to collect, annotate, and standardize datasets that capture the dialectal, sociolinguistic, and orthographic richness of all African languages—an essential step toward improved model equity and real-world utility across the continent's full linguistic spectrum.

6 Data-Performance-Policy Analysis

To understand the relationship between policy, data availability, and performance, we carry out a number of analyses inspired by SAHARA data and empirical results on it.

Data Availability and Diversity. As shown in Figure E3, among the 517 languages in our benchmark, only 45 have more than one dataset, while the majority are represented solely by language identification data. Amharic leads with 11 unique datasets across all clusters, followed by Yorùbá with ten and Hausa with nine. A total of six languages have only one dataset beyond language identification, while the remaining 36 have between two and eight datasets each. *It is important to note that the disparity in dataset availability is closely linked to language policy.* The 45 languages with multiple datasets generally hold official status or are spoken by a significant majority in their respective countries. Government policies that designate certain languages as official often yield greater institutional support, driving increased documentation, education, and media presence. For example, Amharic's official status in Ethiopia contributes to its relatively rich dataset availability, while Yorùbá and Hausa, both widely used in Nigeria for regional governance and media, similarly benefit from enhanced linguistic resources. Conversely, languages lacking official recognition or widespread institutional support receive minimal investment in digital and linguistic infrastructure. The dominance of a few languages within policy frameworks perpetuates data scarcity for many Indigenous African languages, thereby limiting their inclusion in NLP advancements and reinforcing digital inequalities.

It is noteworthy that availability of NLP data is not necessarily determined by the number of speakers and that other variables including language prestige, literacy rates, and economic incentives can be involved. This becomes evident when comparing speaker populations with actual data availability. For example, Hausa (73 million speakers), Swahili (80 million), and Zulu (28 million) are categorized as *hopefuls—languages* with some available labeled datasets. In contrast, Naija (Nigerian Pidgin)—despite having approximately 153 million speakers—is classified as a *left-behind* language (Joshi et al., 2020), largely due to decades of stigmatization and negative public attitudes (Oyebola and Ugwuanyi, 2023), which have significantly contributed to the scarcity of accessible and annotated linguistic resources. Notably, several non-African languages with significantly smaller speaker populations—such as Catalan (5 million), Finnish (10 million), and Swedish (10.5 million)—are regarded as high-resource, primarily as a result of sustained efforts in documentation, digitization, and technological integration. This discrepancy underscores a broader systemic issue in language representation: *it is not just linguistic demographics that shape digital inclusion, but also factors such as historical language prestige, policy decisions, digital infrastructure, and the extent of prior documentation.*

These intersecting factors ultimately determine whether a language is integrated into AI systems or remains marginalized. Addressing this imbalance requires a shift in policy and practice to prioritize equitable digital representation. This includes targeted investments in multilingual data collection, increased funding for research on historically excluded and low-resource languages, and the intentional integration of these languages into education systems, media platforms, and digital technologies. Such efforts must also consider the sociopolitical and infrastructural barriers that shape language inclusion in AI, ensuring that underrepresented languages are not only documented but actively supported within the broader digital ecosystem.

Data Quality. Most of the downstream task datasets are limited to simple tasks that require merely an atomic class label at the word, sentence, or document level (e.g., sentiment analysis, named entity recognition, topic classification). Furthermore, many of these datasets are translations of existing resources or content from high-resource languages like English and French, and they do not always reflect authentic language usage within the respective communities. For instance, AfriXLNI, AfriMMLU, and AfriMGSM (Adelani et al., 2024b) were created by translating XLNI, MMLU, and MGSM into African languages. In

these datasets, the frequent use of borrowed words and phonologized variants of foreign terms (Adebara and Abdul-Mageed, 2022) highlights the challenges posed by cross-lingual concept gaps. When translations are applied to classification tasks, misalignments in the attached labels can occur because labels are not always equivalent across languages. Some labels may not exist in the target language or may have restricted usage. For example, while English possesses a productive set of adjectives, languages like Yorùbá have a more limited adjective inventory that is context-dependent, meaning that an English adjective may be translated as a noun or verb in Yorùbá rather than as an adjective.

Model Performance Here, we analyze performance of our best model, Claude-4-Sonnet. As shown in Figure 2, the model faces varying degrees of difficulty when handling African languages. Figure 2(a) demonstrates that for generation tasks, even the strongest models struggle to produce high-quality text in African languages, with most scores falling below 15 BLEU/ROUGE. In contrast, Figure 2(b) shows that while many languages achieve relatively strong classification performance (over 80% accuracy), a substantial portion still falls into the 60%–80% range, underscoring a clear performance gap. Finally, Figures 2(c) and 2(d) reveal that translation into English is notably easier than translation out of English or French into African languages, where BLEU scores drop from an average of around 19 down to nine or 11, respectively. This finding suggests that even the best model struggles more with producing fluent, faithful output in African languages than with understanding them—underscoring the urgent need for better data and model development tailored to these languages.

Apart from our empirical analyses, the limited availability and diversity of datasets for African languages in NLP benchmarks has significant implications for developing robust language technologies. *Limited Model Performance and Generalization* – Models trained on a single dataset per language risk overfitting to specific domains or styles, reducing their ability to generalize across different contexts, which is especially problematic for African languages with high dialectal variation. *Bias Toward Well-Resourced Languages* – Languages with more datasets naturally perform better in multilingual models, reinforcing disparities and leading to poor performance for underrepresented

African languages. *Restricted Downstream Applications* – Many NLP applications, such as machine translation and question answering, require diverse datasets; if a language is represented only by language identification data, it cannot support the development of more complex language technologies. *Challenges in Transfer Learning* – Transfer learning techniques, like multilingual fine-tuning, rely on cross-lingual similarities and sufficient data; when African languages suffer from sparse training data, they are unable to effectively leverage knowledge transfer from resource-rich languages. We also analyze the performance of Command-A in Figure E2.

7 Recommendations

Policy determines how languages are used across various domains, influencing their visibility and viability in digital spaces. Currently, the limited online presence of many Indigenous African languages restricts the availability of training data, which is crucial for building effective NLP models. We provide the following recommendations:

Policy matters. Governments and policymakers should enact national language policies that mandate the inclusion of Indigenous and underrepresented languages across digital infrastructure, education, and media. Countries with multilingual populations should adopt policies that support the systematic documentation, transcription, and digitization of African languages to enhance their presence in AI applications. Such efforts will enrich the diversity of available data, paving the way for the development of more robust and inclusive models.

Expand data collection and annotation. Given that only 45 of the 517 languages in the benchmark have more than one dataset based on our collection, it is essential to increase the availability of high-quality data for underrepresented African languages across a broad range of downstream tasks. Moreover, prioritizing community-driven data annotation efforts will be crucial in ensuring both linguistic diversity and accuracy, especially for languages that lack institutional support.

Develop contextually relevant and culturally accurate datasets. Many existing African language datasets are derived from translations of high-resource languages, which can introduce misalignments and fail to capture authentic linguistic expressions. To improve NLP performance, datasets should be created using native speakers
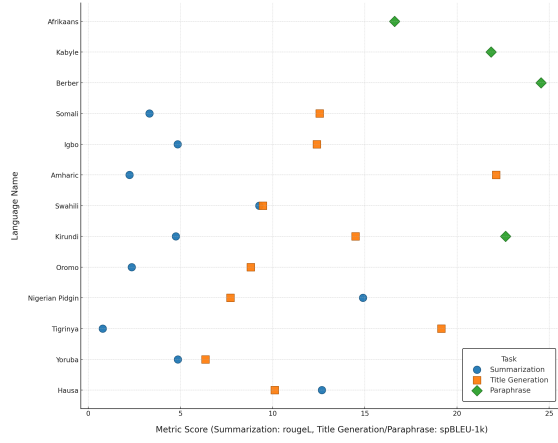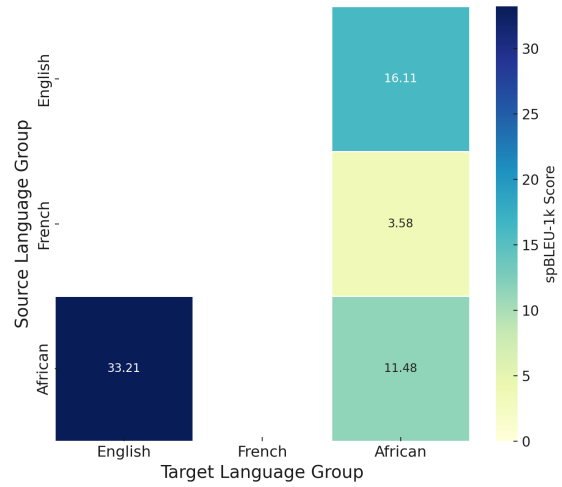
(a) Generation tasks.
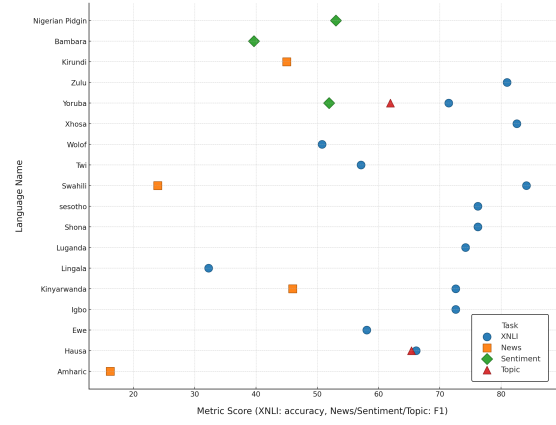
(b) Classification tasks.
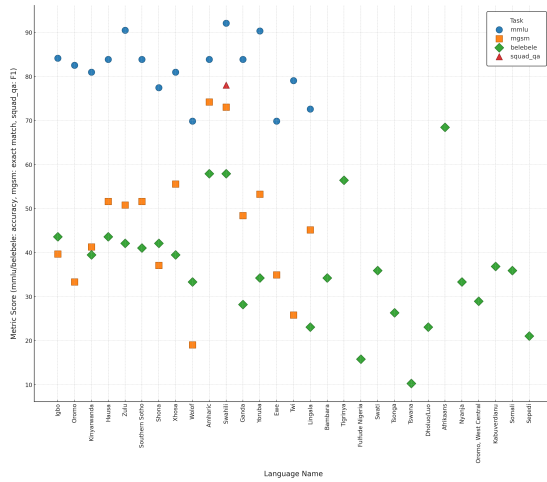
(c) MCCR tasks.

(d) MT tasks grouped.

Figure 2: Distribution of best model performance (Claude-4-Sonnet) on different task clusters across African languages in downstream data.

and sourced from real-world interactions, literature, and media in African languages. This will help preserve linguistic authenticity and avoid the overreliance on loanwords or structures that do not naturally occur in the language. Specialized corpora should also be developed to capture dialectal variations and culturally specific language use.

8 Conclusion

In this work, we set out to unravel how current African language policies, by dictating data availability and accessibility, directly influence model performance across the continent's diverse linguistic spectrum. To achieve this, we conducted a comprehensive empirical evaluation of leading large language models (LLMs) on SAHARA, an extensive benchmark assembled primarily from existing

datasets. SAHARA consists of 30 publicly accessible datasets, covering 16 classification, generation, MCCR, and token level tasks. We also introduced the first publicly available leaderboard for African languages. Our evaluations revealed critical gaps in task performance and language coverage, underscoring pronounced disparities rooted in policy-induced data inequities. Moreover, our findings highlight the importance of integrating theoretical insights on language policies with empirical evaluations to inform forward-thinking policy reforms and promote inclusive data practices. We believe that SAHARA will serve as essential benchmarking standards, catalyzing future research and development efforts aimed at bridging the digital divide and fostering linguistic diversity in artificial intelligence for African communities.

9 Limitations

We identify the following limitations for our work:

1. **Data and Data Availability Bias.** Our benchmark relies on publicly available datasets, which inherently reflect existing biases in language documentation and institutional support. Many Indigenous African languages remain severely underrepresented due to historical policies that prioritize dominant languages. As a result, our findings may not fully capture the linguistic diversity of the continent.

2. **Task Scope.** The evaluation primarily focuses on tasks where data is available, such as language identification and text classification. However, the scarcity of datasets for complex NLP tasks (e.g., machine translation, question answering) limits our ability to assess model performance in broader applications. Future efforts should address this gap by developing more comprehensive datasets across a wider range of tasks.

3. **Model Performance Constraints.** While we analyze the impact of data scarcity on model effectiveness, our study does not explore architectural modifications or fine-tuning strategies that could improve performance for low-resource languages. Further research is needed to examine whether adaptive techniques, such as multilingual pretraining with targeted data augmentation, could mitigate these challenges.

4. **Policy Implementation Challenges.** Our recommendations for policy reforms and inclusive data practices require significant institutional commitment and resources. While we outline actionable steps, their adoption depends on the willingness of governments, research institutions, and technology developers to prioritize African language inclusion in NLP.

Despite these limitations, our work underscores the urgency of addressing data inequities and advocating for policies that foster greater linguistic diversity in AI development.

10 Ethical Considerations

We make the following ethics-related statements about our work:

1. Our research aims to investigate the progress of NLP for African languages, addressing historical language policies that have contributed to data inequities. By improving representation in NLP, we align with broader efforts to foster linguistic diversity in AI, ensuring that African languages are not sidelined in technological advancements.

2. The datasets used in our benchmark are derived from publicly available sources, yet their existence is shaped by historical and contemporary policies that prioritize certain languages over others. We acknowledge that the digital presence of African languages is not merely a technical issue but a policy-driven reality that influences which languages receive institutional support and investment.

3. Although we do not develop models in this work, our findings highlight the impact of policy-induced data disparities on model performance. Addressing these challenges requires policy interventions that support multilingual data collection, equitable resource allocation, and ethical considerations in dataset creation.

4. Proper attribution to dataset authors is not just an academic necessity but a policy imperative for transparency and recognition. To mitigate concerns about data ownership and ethical usage, we provide a publicly accessible reference file citing all datasets included in our benchmark. We strongly encourage researchers and policymakers to acknowledge these sources, reinforcing the importance of ethical and inclusive data practices.

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[6] https://arc.ubc.ca/ubc-arc-sockeye

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Appendices

A   Sahara Task Clusters

A.1   Text Classification

Cross-Lingual Natural Language Inference.
This task involves the classification of 2 given sentences—a premise and a hypothesis into entailment, neutral, or contradiction semantic relation (Adelani et al., 2024b). Adelani et al. (2024b) introduced AfriXNLI, a benchmark for evaluating 15 African Languages on Natural Language Inference (NLI). The languages were translated from the English portion of XNLI (Conneau et al., 2018).

Language Identification.   We include language identification datasets across 518 African languages (Adebara et al., 2022). The dataset includes data from multiple domains including education, government, health care, news, and religion. Additional statistics of the data is available in Table D3. We include language identification tasks to investigate **(1.)** the capabilities of language models in correctly generating the appropriate language names of an input text and **(2.)** Correctly generate an additional sentence in a specific language. We include these two approaches because many languages have multiple names (Chen et al., 2024) and a LM's inability to appropriately name a language does not implicate a lack of information about the language.

News Classification.   This task involves automatically categorizing news articles into predefined categories or topics based on their content. The goal is to leverage machine learning and NLP techniques to understand and organize large volumes of news data, making it easier for users to access relevant information. News classification plays a crucial role in information retrieval, content recommendation, and other applications that involve organizing and categorizing textual data. The news classification cluster consists of data from four languages including Amharic (Azime and Mohammed, 2021), Kinyarwanda (Niyongabo et al., 2020), Kirundi (Niyongabo et al., 2020), and Swahili (David, 2020a,b). Table D3 provides additional details of the data in this cluster.

Sentiment Analysis.   Sentiment analysis is crucial in gaining insights into public opinion, customer feedback, and user sentiments across various platforms. The sentiment analysis cluster consists

of the Bambara Sentiment dataset (Diallo et al., 2021), YOSM–a Sentiment Corpus for Movie Reviews in Yorùbá (Shode et al., 2022b), and the Nigerian Pidgin sentiment dataset (Oyewusi et al., 2020), respectively. Further details about the statistical composition of this data is available in Table D3.

Topic Classification.   The primary goal for this task is to automatically categorize the content of the text based on its theme. Topic classification is widely used in various applications, such as document organization, content recommendation, and information retrieval. We include topic classification datasets for Yorùbá and Hausa (Hedderich et al., 2020).

A.2   Text Generation

Machine Translation.   A robust benchmark for MT tasks is essential. SAHARA, in its quest to effectively assess machine translation for African languages, selectively incorporates datasets containing diverse African languages into its benchmark. Specifically, SAHARA includes datasets such as Pidgin-UNMT[7] (Ogueji and Ahia, 2019), Afro-MT[8] (Reid et al., 2021a), Lafand-MT (Adelani et al., 2022a), SALT[9] (Akera et al., 2022), and HornMT, thus encompassing a total of 45 language pairs.

Paraphrase.   Paraphrasing is a core task in NLG that revolves around the comprehension and generation of text that conveys the same meaning while possibly exhibiting differences in structure, phrasing, or style (Chen et al., 2023). SAHARA incorporates the TaPaCo dataset (Scherrer, 2020), which is publicly accessible and covers a total of 73 languages, including four of African origin. These African languages consist of Kirundi, Amazigh, a macro-language Berber, and Afrikaans.

Summarization.   Summarization is the task of creating a condensed version of a text that retains its core ideas and essential information (Nallapati et al., 2016). In the context of SAHARA, our focus primarily centers on a subset of the abstractive summarization dataset, XL-SUM (Hasan et al., 2021), which includes several African languages: Amharic, Hausa, Igbo, Kirundi, Oromo, Pidgin,

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[7]PidginUNMT GitHub Link
[8]AfroMT GitHub Link
[9]SALT GitHub Link

Somali, Swahili, Tigrinya, and Yoruba. Additionally, we have extended our dataset collection efforts by scraping non-overlapping summarization datasets from BBC and Voice of Africa (VoE) websites, specifically targeting three African languages: Hausa, Ndebele, and Swahili.

Title Generation. The task of title generation in NLG involves generating a concise and meaningful title or headline for a given article. This task shares its dataset source with summarization, drawing from XL-SUM, and also includes dataset extensions from BBC and VoE with focus on enabling zero-shot title generation.

A.3 Multiple-Choice, Comprehensive and Reasoning

This task cluster majorly addresses *Question Answering* type questions. The QA tasks in this cluster are more mathematical-reasoning and reading-comprehension-oriented.

Mathematical Word Problems. (Adelani et al., 2024b) introduced AfriMGSM, a QA dataset that contains human-written grade school mathematical word problems. Their dataset covers 15 African Languages, and the translation of each question to English for each language for in-language evaluation of LLMs. In this task, given a word problem, the LLM is expected to return a numerical value as output.

General Knowledge QA. (Adelani et al., 2024b) introduced AfriMMLU, a multi-choice QA dataset covering 5 areas of knowledge in 15 African Languages. The knowledge areas are high-school geography, high-school microeconomics, elementary mathematics, international law), and global facts. In this task given a question in any of the aforementioned areas, and 4 options, the LLM is expected to choose the right option.

Reading Comprehension QA. In this task, the LLMs are evaluated based on their ability to understand information in a given article. (Bandarkar et al., 2024b) introduced a parallel reading comprehension dataset covering 122 languages, 23 of which are native to Africa. The dataset comprises of short paragraphs accompanied by multi-choice Questions, whose answers can be inferred from accompanying paragraphs.

Context-based Question-Answering. QA represents another vital facet of NLG, focusing on a model's capability to provide answers based on integrated knowledge. SAHARA relies on the gold passage dataset from the multilingual TYDIA[10] QA resource (Clark et al., 2020). This dataset offers concise questions with precisely one corresponding answer, enabling rigorous evaluation of QA performance.

A.4 Tokens-level Classification

Named Entity Recognition. We incorporate NER datasets across 30 languages. We use Distance Supervision NER (DS NER) Data (Hedderich et al., 2020), MasakhaNER (Adelani et al., 2022b), WikiAnn (Rahimi et al., 2019), Yoruba-Twi NER (Alabi et al., 2020b), and multiple NER data from SADiLaR. Additional details about the datasets are available in Table D3.

Phrase Chunking. This task involves identifying and grouping together consecutive words or tokens into meaningful syntactic units, known as phrases. These phrases can include noun phrases, verb phrases, prepositional phrases, and other grammatical structures. The goal of phrase chunking is to analyze the grammatical structure of a sentence and extract higher-level syntactic units for better understanding. The phrase chunking cluster consists of data for ten Indigenous languages of South Africa (see Table D3). The data has annotations for noun, verb, adjective, adverbial, and prepositional phrase chunks. Words not belonging to these phrase types are labelled with the tag *O*.

Part of Speech Tagging. This classification task involves assigning grammatical categories or labels (such as noun, verb, adjective) to each word in a sentence. The primary goal of POS tagging is to analyze the syntactic structure of a sentence and understand the role of each word within it. POS tagging is crucial for various NLP applications, as it provides a foundation for more advanced linguistic analysis. We include datasets for Igbo taken from IgboNLP (Onyenwe et al., 2019).

B Benchmark

Table B1 shows the comparison between SAHARA with other benchmarks.

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[10]TyDiQA GitHub Link

Category	Benchmark	Reference	Lang/Total	Tasks
Multilingual	FLoRES200	(Costa-jussà et al., 2022)	52/200	1
	GEM$_{v1}$	(Gehrmann et al., 2021)	10/52	5
	GEM$_{v2}$	(Gehrmann et al., 2021)	10/52	9
	NLLB M.D.	(Costa-jussà et al., 2022)	2/8	1
	NLLB S.D.	(Costa-jussà et al., 2022)	2/8	1
	SIB-200	(Adelani et al., 2024a)	46/200	1
	Toxicity200	(Costa-jussà et al., 2022)	50/200	1
	XGLUE	(Liang et al., 2020)	1/19	3
	XTremE	(Hu et al., 2020)	2/40	4
Language-specific	BanglaNLP$_{v1}$	(Bhattacharjee et al., 2023)	1	6
	CLUE	(Xu et al., 2020)	1	6
	CUGE	(Yao et al., 2021)	1	8
	Dolphin	(Nagoudi et al., 2023)	1	13
	FLUE	(Le et al., 2020)	1	5
	IndoNLU	(Wilie et al., 2020)	1	5
	IndoNLG	(Guntara et al., 2020)	1	6
	JGLUE	(Kurihara et al., 2022)	1	3
	KorNLU	(Ham et al., 2020)	1	2
	LOT	(Guan et al., 2022)	1	4
	ORCA	(Elmadany et al., 2023)	1	7
	PhoMT	(Doan et al., 2021)	1	1
African	AfriSenti	(Muhammad et al., 2023a)	14	1
	AfroMT	(Reid et al., 2021b)	8/8	1
	AfroNLG	(Adebara et al., 2024b)	517/517	6
	AfroNLU	(Adebara et al., 2023)	28/28	7
	Horn-MT	—	3/3	1
	Iroko-Bench	(Adelani et al., 2024b)	16/16	3
	Mafand-MT	(Adelani et al., 2022a)	17/17	1
	Menyo-20k	(Adelani et al., 2021b)	1/1	1
	Naija-senti	(Muhammad et al., 2022)	4/4	1
	🐘 SAHARA	ours	517/517	16

Table B1: A Comparison of SAHARA with other Benchmarks. **M.D:** Multilingual domain, **S.D:** Seed Data.

C Few-shot prompt example

Figure C1 shows an example for MT task.

D Dataset Description

Table D2 describes all datasets included in SA-HARA.

E Data-Performance-Policy Analysis

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Compelete the translation of the last sentence from Tigrinya text to Somali
Text: እቲ ብዮርካ አስናዳኢ ኩነት ዝተዳለወ ምርኢት ''አዲስ ኮንሰርት'' ብዝብል ስያሜ እዩ ከቐርብ።
Translation: Waxaa soo abaabulay qabanqaabiyaha xaflada Yorka bandhig faneedkan
cinwaankeedu waa "Concert Addis".
Text: ነጥብ መቝይሮ ውዕ� ክመዝግቡ ናይዝኽእሉ ምህዞታት አካልን አብ ቀረባ እዋን ዝተረኸበን እዚ. ምህዞ አብ ሐደ ዙርያ ጉያ ካብ
ፍርቄ ሰከንድ ክሳብ ሐደ ሰከንድ ምምሕያሽ ከምዕኡ ዝኽእል ተባሂሉ ይእመንን።
Translation: Waxa ay ahayd tii ugu dambaysay ee bandhigyo cajiib ah oo lagu
sameeyay tignoolajiyada ciyaarta beddeleysa, taas oo lagu tiriyo in ay horumariso
waxqabadka inta u dhaxaysa nus ilbiriqsi iyo ilbiriqsi.
Text: ዓለማዊ ውድብ ጥዕና ዝርጌሐ ፖልዮ አህጉራዊ ህጽጽ ኩነታት ጥዕና ህዝቢ. ምኽኑ ገሊጹ።
Translation: Ururka Caafimaadka Adduunka ayaa sheegaya in faafitaanka cudurka
dabayshu ay tahay xaalad caafimaad oo degdeg ah oo caalami ah.
Text: በዓል ጌድ አል አድУ አብ ከተማታት ጄማ፣ ሃዋሳን ደሴን አብ ደገን አብ ውሽጢ. ዝሃነ ብዝ ተኸየዱ ሃይማኖታዊ ስርዓታት ተኸበሩ።
Translation: Magaalooyinka Jimma, Hawassa, iyo Dessie ayaa sido kale si wanagsan
loogu ciiday munaasabada Ciidul Adxaa oo isugu jirta dhacdooyin lagu qabtay gudaha
iyo dibadba.
Text: መገዲ አየር ማሌይኸ የ አብ ዒ. ዓመት ብሓደጋ ኽልተ ነፈርቱ ድሕሪ ምስኣኑ መሓ ዊ ምምዕ Continued ንምግባር 6000 ሰራሕተኛታት
ክንክ ከምዝ አፍሊ ።
Translation: Shirkada dayaaradaha ee Malaysiya ayaa ku dhawaaqday inay shaqada
kajoojinayaan shaqaale dhan 6000 taas oo ay sababtay dib u habayn kadib markii ay
sannadkan laba diyaaradood ku waayeen musiibooyin.
Text: ቀዳማይ ሚኒስተር ፓኪስታን፣ ራጃ በርዊ አሽሪፍ፣ አንጻር ፕሬዚደንት አሲፍ ዓ. ዘርዳ ናይ ብልሽ ና መርመራታ ንምኽፋ
ብ ። ምፍሻ አብ ቅድሚ ላዕ ወ Beit ፍርዲ ፓኪስታ ቀሪ ።
Translation:
```

| Dataset	Brief Description	African Language(s)
MasakhaNER (Adelani et al., 2021a), (Adelani et al., 2022c)	Curated for Named Entity Recognition for several African Languages	amh, bam, bbj, ewe, fon, hau, ibo, kin, lug, luo, mos, nya, pcm, sna, swa, tsn, twi, wol, xho, yor, zul
MasakhaPOS (Dione et al., 2023a)	Curated from News sources and publicly available datasets for Part-Of-Speech Tagging	bam, bbj, ewe, fon, hau, ibo, kin, lug, luo, mos, nya, pcm, sna, swa, tsn, twi, wol, xho, yor, zul
MAFAND-MT (Adelani et al., 2022a)	African news corpus for Machine Translation	bam, bbj, ewe, fon, hau, ibo, lug, luo, mos, swa, tsn, twi, wol, xho, yor, zul
XL-Sum Hasan et al. (2021)	Curated for Summarization and Title Generation	amh, ibo, orm, run, swa, yor, hau, pcm, som, tir
YorubaSenti (Orimaye et al., 2012)	Curated from comments on movies on YouTube	yor
TaPaCo (Scherrer, 2020)	Developed to provide example sentences and translations for particular linguistic constructions and words	afr, ber, run , zgh
TyDi QA (Clark et al., 2020)	Curated for Information-Seeking QA tasks	swa
HornMT	Parallel MT dataset curated for languages in Horn of Africa	aaf, amh, orm, som, tir
yoruba-twi-ner (Alabi et al., 2020a)	Curated for evaluating embeddings for low-resource languages	yor, twi
KINNEWS and KIRNEWS (Niyongabo et al., 2020)	Curated for multi-class classification of news articles	kin, run
AmharicNews (Azime and Mohammed, 2021)	Curated for text classification from news articles	amh
SwahiliNews v0.2 (David, 2020a)	Curated for text classification from news articles	swa
Bambara (Diallo et al., 2021)	Curated for Sentiment Analysis through web crawling	bam
IgboNLP(Onyenwe et al., 2018b)	Contains text corpus, POS tagset and POS-tagged subcorpus	ibo
yosm (Shode et al., 2022a)	Curated from movie reviews for Sentiment Analysis	yor
pidgin-tweet (Oyewusi et al., 2020)	Curated for SA from tweets	pcm
WikiAnn (Pan et al., 2017), (Rahimi et al., 2019)		afr, amh, ibo, mlg, kin, som, swa, yor
HausaTopic,YorubaTobic (Hedderich et al., 2020)	Curated for Topic Classification	hau, yor
SaDiLAR (Eiselen, 2016)	Curated for NER of 10 South African Languages	afr, nbl, nso, sot, ssw, tsn, tso, ven, xho, zul
AfriSenti (Muhammad et al., 2023a)	Curated for African tweet sentiment analysis	amh, ALG-ara, hau, kin, ibo, MOR-ara, MOZ-por, pcm,form, swa, tir, twi,tso,yor
Afro-MT (Reid et al., 2021a)	Benchmark for MT of 8 African Languages	afr, bem, lin, run, sot, swa, xho, zul
PidginUNMT (Ogueji et al., 2021)		pcm
SALT (Akera et al., 2022)	Curated for Parallel MT of 5 Ugandan Languages	ach, lgg, lug, nyn, teo
Cheetah (Adebara et al., 2024b)	Summarization test set	hau, nde, swa
Cheetah (Adebara et al., 2024b)	Title generation test set	amh, gag (zero-shot), hau, ibo, pcm, som, swa, tir, yor, kin (zero-shot), afr, mlg (zero-shot), orm, nde (zero-shot), sna(zero-shot)
NCHLT-NER (Eiselen, 2016)	Named Entity Recognition	afr, nbl, nso, sot, ssw, tsn, tso, ven, xho, zul
BeleBele (Bandarkar et al., 2024b)	Reading Comprehension MCQA	afr amh, bam, fuv, gaz, hau, ibo,kea,kin, lin, lug, luo,nso, nya, sna ,som, sot, ssw, swh, tir, tsn, tso, wol, xho, yor,zul
IrokoBench (Adelani et al., 2024b)	MGSM,MMLU,XNLI	amh, ewe, hau, ibo,kin, lin, lug, orm, sna ,sot, swa, tir, wol, xho, yor,zul

Table D2: A description of all datasets included in *Sahara*. **ALG:** Algerian, **MOR:** Moroccan, **MOZ:** Mozambican.

Task	Source	Language	Train/ Dev/ Test
MT	(Adelani et al., 2022a)	eng-hau	5.9K/ 1.3K/ 1.5K
		eng-ibo	6.9K/ 1.5K/ 1.4K
		eng-lug	4.1K/ 1.5K/ 1.5K
		eng-pcm	4.8K/ 1.5K/ 1.6K
		eng-swa	30.8K/ 1.8K/ 1.8K
		eng-tsn	2.1K/ 1.3K/ 1.5K
		eng-twi	3.3K/ 1.3K/ 1.5K
		eng-yor	6.6K/ 1.5K/ 1.6K
		eng-zul	3.5K/ 1.5K/ 1.0K
		fra-bam	3.0K/ 1.5K/ 1.5K
		fra-bbj	2.2K/ 1.1K/ 1.4K
		fra-ewe	2.0K/ 1.4K/ 1.6K
		fra-fon	2.6K/ 1.2K/ 1.6K
		fra-mos	2.5K/ 1.5K/ 1.6K
		fra-wol	3.4K/ 1.5K/ 1.5K
	(Reid et al., 2021a)	eng-afr	25.8K/ 3.2K/ 3.2K
		eng-bem	12.0K/ 1.5K/ 1.5K
		eng-lin	17.7K/ 2.2K/ 2.2K
		eng-run	12.5K/ 1.6K/ 1.6K
		eng-sot	28.8K/ 3.6K/ 3.6K
		eng-swa	28.1K/ 3.5K/ 3.5K
		eng-xho	26.1K/ 3.3K/ 3.3K
		eng-zul	29.1K/ 3.6K/ 3.6K
	(Ogueji and Ahia, 2019)	eng-pcm	1.7K/ 0.2K/ 0.2K
	(Akera et al., 2022)	All-pairs[1]	20.0K/ 2.5K/ 2.5K
	HornMT	All-pairs[2]	1.7K/ 0.2K/ 0.2K
NER	(Adelani et al., 2021a)	See Table D2	41.2K/ 5.1K/ 5.1K
	(Adelani et al., 2022c)	See Table D2	41.2K/ 5.1K/ 5.1K
	(Eiselen, 2016)	See Table D2	1.7M/ 219.7K/ 215.6K
	(Alabi et al., 2020a)	See Table D2	20.2K/ 2.8K/ 5.5K
	(Pan et al., 2017)	See Table D2	9.2K/ 9.2K/ 9.4K
News	(Azime and Mohammed, 2021)	amh	41.2K/ 5.1K/ 5.1K
	(Niyongabo et al., 2020)	kin	15.3K/ 1.7K/ 4.3K
		run	3.3K/ 0.4K/ 0.9K
	(David, 2020a)	swa	4.4K/ 0.6K/ 0.6K
Paraphrase	(Scherrer, 2020)	amh, ber, kab, run	22.4K/ 2.8K/ 2.8K
		ber	17.6K/ 2.2K/ 2.2K
		kab	4.4K/ 0.6K/ 0.6K
Phrase Chunking	(Eiselen, 2016)	See Table D2	107.5K/ 13.0K/ 13.4K
POS Tagging	(Onyenwe et al., 2018a, 2019)	ibo	756.8K/ 94.7K/ 95.0K
Question Answering	(Clark et al., 2020)	swa	49.9K/ 0.5K/ n/a
Sentiment Analysis	(Diallo et al., 2021)	bam	2.4K/ 0.3K/0.3K
	(Oyewusi et al., 2020)	pcm	11.2K/ 1.4K/ 1.4K
	(Shode et al., 2022a)	yor	0.8K/ 0.2K/ 0.5K
Summarization	(Hasan et al., 2021)	amh	5.8K/ 0.7K/ 0.7K
		ibo	4.2K/ 0.5K/ 0.5K
		orm	6.1K/ 0.8K/ 0.8K
		Rundi	5.7K/ 0.7K/ 0.7K
		swa	7.9K/ 1.0K/ 1.0K
		yor	6.4K/ 0.8K/ 0.8K
		hau	6.4K/ 0.8K/ 0.8K
		pcm	9.2K/ 1.2K/ 1.2K
		som	6.0K/ 0.7K/ 0.7K
		Tigrinya	5.5K/ 0.7K/ 0.7K
	(Adebara et al., 2024b)	⋆†	-/ -/ 0.4K
Title Generation	(Hasan et al., 2021)	amh	5.8K/ 0.7K/ 0.7K
		ibo	4.2K/ 0.5K/ 0.5K
		orm	6.1K/ 0.8K/ 0.8K
		run	5.7K/ 0.7K/ 0.7K
		swa	7.9K/ 1.0K/ 1.0K
		yor	6.4K/ 0.8K/ 0.8K
		hau	6.4K/ 0.8K/ 0.8K
		pcm	9.2K/ 1.2K/ 1.2K
		som	6.0K/ 0.7K/ 0.7K
		Tigrinya	5.5K/ 0.7K/ 0.7K
	(Adebara et al., 2024b)	⋆	-/ -/ 5.9K
Topic Classification	(Hedderich et al., 2020)	hau	2.0K/ 0.3K/0.6K
		yor	1.3K/ 0.2K/ 0.4K

Table D3: Statistics of the data in our benchmark. $All - pairs^1$ each have the same size of data. They include ach-eng, ach-lgg, ach-lug, ach-nyn, ach-teo, ach-teo, eng-lgg, eng-lug, eng-nyn, eng-teo, lgg-teo, lug-lgg, lug-teo, nyn-lgg, nyn-lug, and nyn-teo. $All - pairs^2$ are all possible language combinations of aaf, amh, orm, som, tir, eng. $\star^\dagger$ is a summarization test set including 'hau', 'nde' (zero-shot), and 'swa'. $\star$ is a title generation test set across 15 languages: 'amh', 'gag' (zero-shot), 'hau', 'ibo', 'pcm', 'som', 'swa', 'tir', 'yor', 'kin' (zero-shot), 'afr', 'mlg' (zero-shot), 'orm', 'nde' (zero-shot), 'sna'(zero-shot).
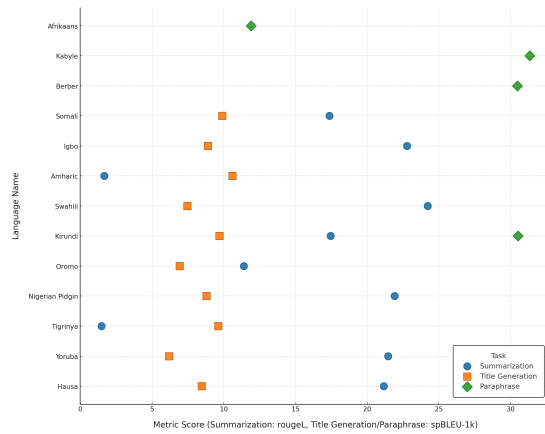
(a) Generation tasks.
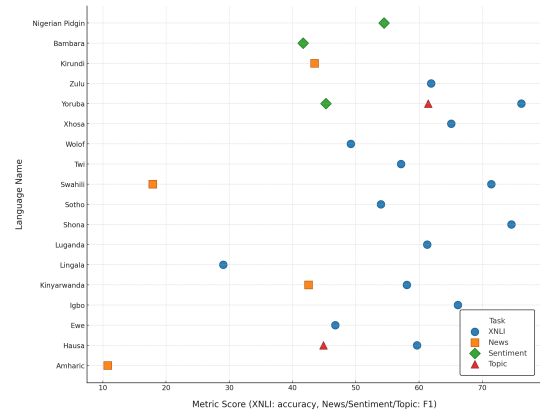
(b) Classification tasks.
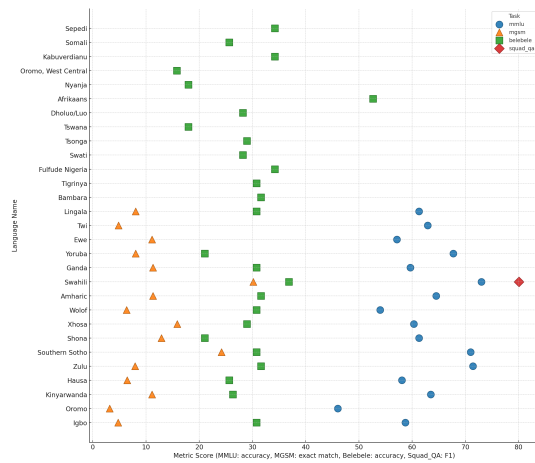
(c) MCCR tasks.
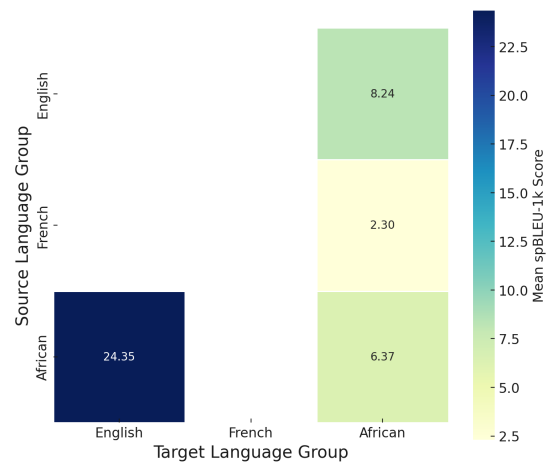
(d) MT tasks grouped.

Figure E2: Distribution of best open weight model performance (`Command-A`) on different task clusters across African languages in downstream data.
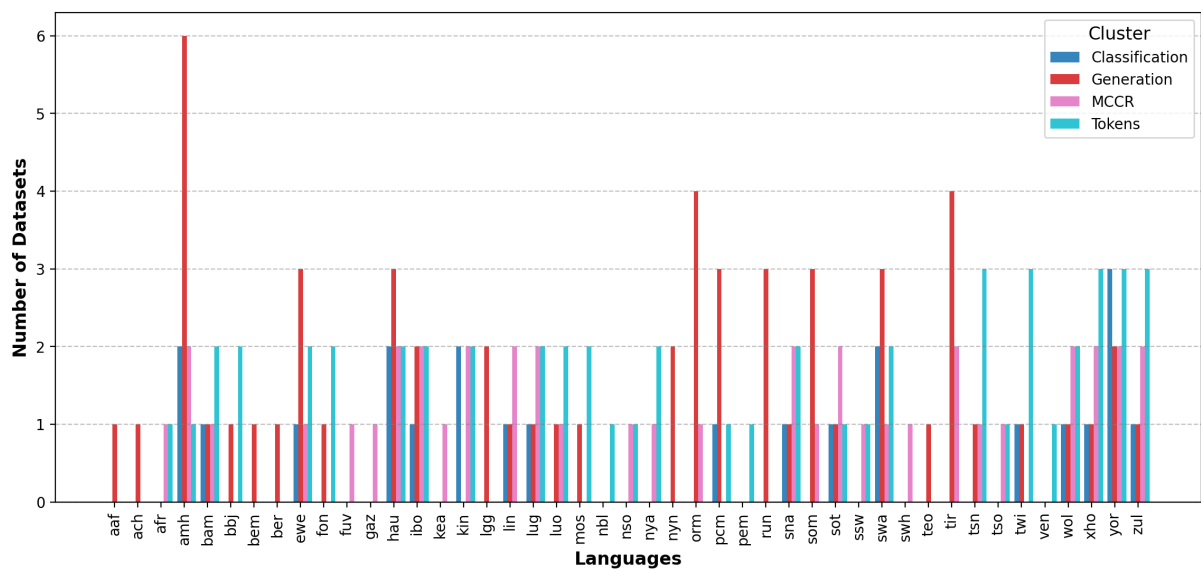
Figure E3: Distribution of languages across different clusters. Each bar represents the number of datasets a language appears in, categorized into the clusters, with some languages appearing in all four clusters while others are only present in one or two.
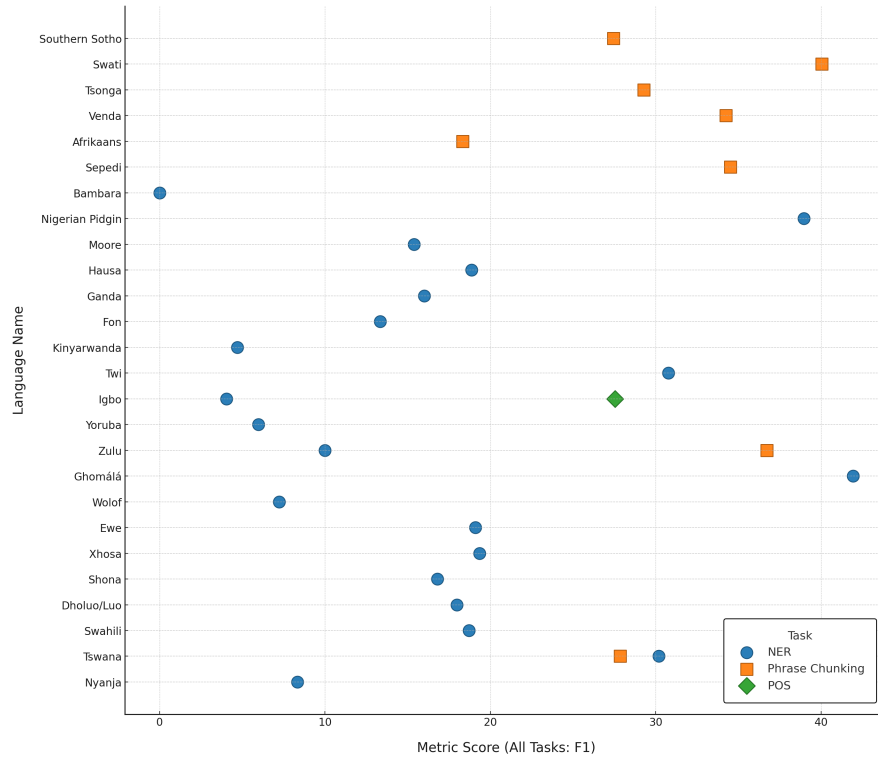
(a) Command-A performers.
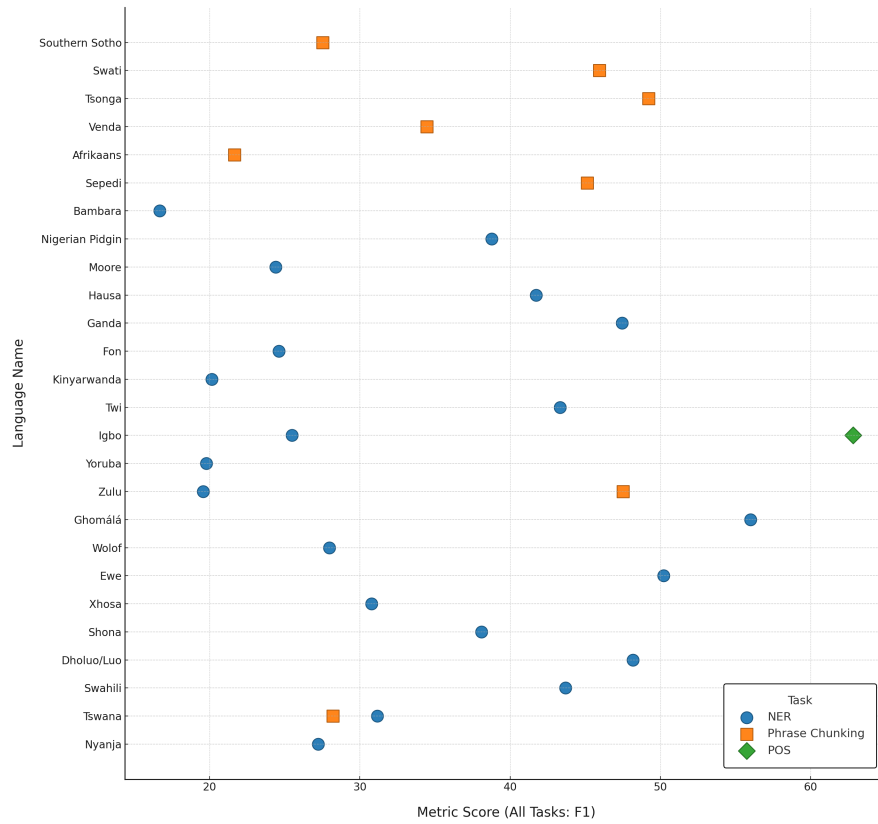
(b) Claude-4-Sonnet performance.

Figure E4: Performance of `Command-A` and `Claude-4-Sonnet` on token-level task cluster across African languages in downstream data.

Table E4 — Few-shot evaluation across different task clusters/tasks.

Cluster	Identifier	Metric	Shots	S₁	S₂	S₃	S₄	S₅	S₆	L₁	L₂	L₃	L₄	L₅	L₆	L₇	L₈	L₉	L₁₀	L₁₁	L₁₂	L₁₃	L₁₄	L₁₅	L₁₆	CL₁	CL₂
Classification	xlni	Acc.	5	33.6	33.7	36.7	41.18	40.4	46.68	48.08	55.06	34.3	40.69	37.09	61.09	57.86	65.58	44.2	38.19	51.89	48.38	52.09	35.87	46.77	59.67	69	**69.6**
	lid	F₁	10	0	0	0.87	0.26	0.85	0.77	2.82	3.6	0	1.49	2.27	1.95	**4.61**	4	1.81	3.34	3.26	3.07	3.3	3.05	3.32	4.57	3.73	4.48
	news	F₁	3	0.86	0.35	0.15	17.54	0	6.64	21.94	0	2.06	24.06	0.12	25.83	7.83	35.56	28.03	0.61	35.26	33.31	34.81	3.45	30.46	28.66	**40.09**	32.19
	sentiment	F₁	5	38.51	24.75	30.45	11.05	28.77	1.99	36.09	42.47	38.4	28.36	36.07	34.56	20.55	46.35	35.86	25.94	24.51	45.82	35.89	19.98	37.07	47.14	55.67	**57.52**
	topic	F₁	3	8.73	31.62	20.3	19.79	12.46	17.15	48.11	39.35	34.95	28.55	42.12	44.3	31.8	70.73	36.47	43.74	64.89	56.48	48.73	52.09	50.96	53.16	67.93	**76.57**
	Avg.			16.34	18.08	17.69	17.96	16.50	14.65	31.41	28.10	21.94	24.63	23.53	33.55	24.53	44.44	29.27	22.36	35.96	37.41	34.96	22.89	33.72	38.64	47.28	**48.07**
Generation	mt_eng2xx	spBleu¹ᴷ	5	1.79	3.63	3.45	3.25	2.12	3.4	7.07	7.61	1.72	4.37	2.79	6.24	6.91	4.56	3.73	3.29	8.84	8.7	9.36	1.4	6.06	8.22	12.18	**12.36**
	mt_fra2xx	spBleu¹ᴷ	5	0.79	0.36	0.74	1.05	1.25	1.32	0.73	0.95	0.7	1.19	0.66	2.03	1.67	2.05	1.15	0.82	1.93	1.87	1.77	1.05	1.04	2.3	3.41	**3.42**
	mt_xx2xx	spBleu¹ᴷ	5	0.4	0.45	0.42	0.42	0.36	0.18	0.43	0.63	0.72	0.55	0.46	0.71	0.9	1.39	0.55	0.17	1.28	1.05	1.37	0.67	0.38	0.85	**5.15**	4.44
	paraphrase	spBleu¹ᴷ	5	23.2	28.88	31.15	19.12	25.93	17.85	28.73	25.83	31.68	31.33	23.66	17.26	21.34	15.37	32.13	30.68	26.86	19.64	27.79	19.23	**36.06**	26.06	23.2	20.35
	summary	rougeL	2	10.03	3.24	4.37	10.07	0.91	13.34	15.1	10.43	1.45	12.74	5.92	16.16	15.73	17.13	13.27	4.19	16.92	17.19	16.4	15.46	14.88	16.09	5.99	16.3
	title	spBleu¹ᴷ	2	2.14	2.81	0.25	2.3	0.03	5.78	7.48	5.78	3	5.94	1.58	7.75	7.51	8.65	6.83	3.2	11.07	10.34	8.78	7.32	6.69	8.65	**13.62**	9.48
	Avg.			6.39	6.56	6.73	6.04	5.10	6.98	9.92	8.54	6.55	9.35	5.85	8.36	9.01	8.19	9.61	7.06	**11.15**	9.80	10.91	7.52	10.85	10.36	10.59	11.06
MCCR	mmlu	Acc.	5	24.09	28.5	28.68	27.29	28.9	30.99	31.88	40.9	26.4	44.51	22.1	42.09	44.9	60.71	51.5	24	56.51	59.3	50.42	59.81	29.8	**61.91**	81.6	58.6
	mgsm	ExactM	5	2.6	3.21	0	1.2	3.39	0.7	2.9	2.8	3.3	2.7	1.5	2.3	5.3	0.6	4.4	3	10.1	7.51	7.6	4.5	4.39	1.1	**45.9**	29.5
	belebele	Acc.	5	27.71	14.71	25.2	29.31	31.31	24.69	22.7	26.93	25.09	28.24	26.33	25.63	31.04	32.34	33.64	26.61	30.4	35.92	33.72	30.83	20.99	29.12	36.6	**39.7**
	squad_qa	F₁	5	57.45	70.89	67.32	43.13	71.31	74.97	78.04	80.91	52.66	59.48	63.41	73.78	**82.49**	79.16	69.25	64.64	77.65	76.35	66.25	53.92	74.64	80.05	78.02	76.11
	Avg.			27.96	29.33	30.30	25.23	33.73	32.84	33.88	37.89	26.86	33.73	28.34	35.95	40.93	43.20	39.70	29.56	43.67	44.77	39.50	37.27	32.46	45.55	**60.53**	50.98
Tokens	ner	F₁	5	0	0.78	1.76	2.99	0.13	3.65	2.26	7.49	2.35	3.96	0.2	6.03	13.14	11.4	8.51	1.52	6.86	10.54	8.64	6.04	4.3	16.88	**35.06**	27.04
	phrase	F₁	5	14.79	28.5	29.44	11.52	24.91	27.73	15.95	29.35	29.42	16.55	30.87	13.59	30.01	23.97	26.34	23.09	25.55	23.13	16.78	25.13	29.44	31.05	**36.69**	36.45
	pos	F₁	5	8.83	6.73	10.56	8.04	10.3	10.46	9.13	13.2	9.81	11.68	12.52	13.86	19	13.99	18.36	11.4	14.13	15.04	11.52	20.76	13.71	27.54	**62.84**	38.67
	Avg.			7.87	12.00	13.92	7.52	11.78	13.95	9.11	16.68	13.86	10.73	14.53	11.16	20.72	16.45	17.74	12.00	15.51	16.24	12.31	17.31	15.82	25.16	**44.86**	34.05
	Overall			14.64	16.49	17.16	14.19	16.78	17.10	21.08	22.80	17.30	19.61	18.06	22.25	23.80	28.07	24.08	17.75	26.57	27.05	24.42	21.25	23.21	29.93	**40.82**	36.04

Table E4: Few-shot evaluation across different task clusters/tasks. The highest score for each individual task is in **bold green**, while the best average score across each task cluster (and **overall** score, calculated as average of task cluster averages) is in **bold orange**. **Underline**: refers to the best score across the open source/weights LLMs.

Shots: number of shots. **SLMs: S_1** Llama3.2 (1B), **S_2** Gemma2 (2B), **S_3** Llama3.2 (3B), **S_4** Phi-3.5 (3.8B), **S_5** Phi-4 (3.8B), and **S_6** Gemma3 (4B). **LLMs: L_1** Llama3.1 (8B), **L_2** Gemma2 (9B), **L_3** Aya (8B), **L_4** Aya (8B), **L_5** Babel (9B), **L_6** Command-R-Plus-R7B (8B), **L_7** Gemma3 (12B), **L_8** Gemma2 (27B), **L_9** DeepSeek-R1-Distill-Qwen (32B), **L_{10}** Aya (35B), **L_{11}** Llama3.1 (70B), **L_{12}** Llama3.3 (70B), **L_{13}** DeepSeek-R1-Distill-Qwen (70B), **L_{14}** Babel (83B), **L_{15}** Command-R-Plus (104B), **L_{16}** Command-A (111B). **Closed LLMs: CL_1** Claude-4-Sonnet, **CL_2** GPT-4.1.