Blessing of Multilinguality: A Systematic Analysis of Multilingual In-Context Learning

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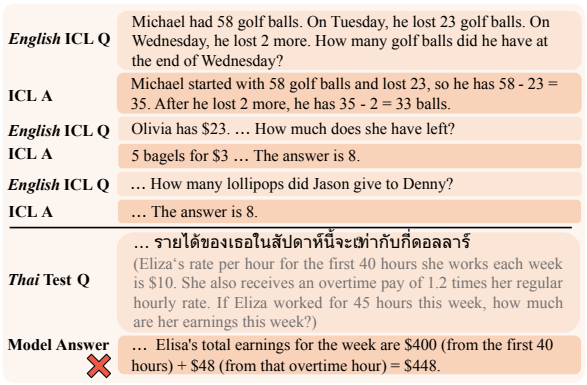
Abstract

While multilingual large language models generally perform adequately, and sometimes even rival English performance on high-resource languages (HRLs), they often significantly underperform on low-resource languages (LRLs; Costa-jussà et al., 2022). Among several prompting strategies aiming at bridging the gap, multilingual in-context learning (ICL; Shi et al., 2023) has been particularly effective when demonstration in target languages is unavailable. However, there lacks a systematic understanding when and why it works well.

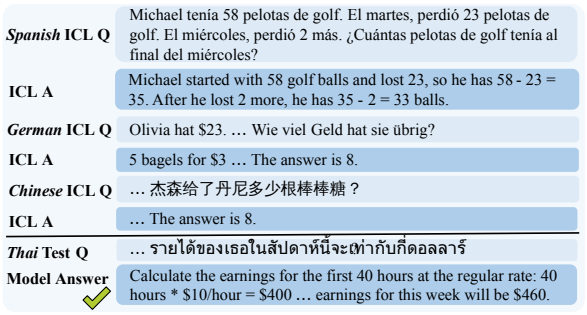
In this work, we systematically analyze multilingual ICL, using demonstrations in HRLs to enhance cross-lingual transfer. We show that demonstrations in mixed HRLs consistently outperform English-only ones across the board, particularly for tasks written in LRLs. Surprisingly, our ablation study show that the presence of irrelevant non-English sentences in the prompt yields measurable gains, suggesting the effectiveness of multilingual exposure itself. Our results highlight the potential of strategically leveraging multilingual resources to bridge the performance gap for underrepresented languages.

1 Introduction

In-context learning (ICL; Brown et al., 2020) has become a widely adopted technique in natural language processing with large language models (LLMs; Touvron et al., 2023; Chowdhery et al., 2023; Dubey et al., 2024; Yang et al., 2024a,b, *inter alia*), which enables LLMs to learn to solve problems by analogy from a few input-output examples (i.e., demonstrations) without updating model parameters. As a generic method, ICL has also been effective in improving the cross-lingual performance of multilingual LLMs (MLLMs; Winata et al., 2021; Ahuja et al., 2023; Shi et al., 2023; Razumovskaia et al., 2024; Asai et al., 2024).



(a) `English` ICL Mode



(b) `Multilingual` ICL Mode

Figure 1: Illustration of two ICL modes. After providing a few-shot prompt, we evaluate LLM on the same domain in various languages. In a controlled experiment, each demonstration in (a) and (b) shares the same meaning albeit in different languages. Contents and languages of demonstrations are randomly sampled from a training set and a preset high-resource language list, respectively. We find that `Multilingual` ICL mode (b) are more effective in helping the LLM solve tasks in different languages compared to `English` ICL mode (a).

Prior work has introduced two common ICL strategies for non-English languages: (i) translating the target question into English and performing English-only ICL (Shi et al., 2023; Ahuja et al., 2023; Razumovskaia et al., 2024, *inter alia*), and (ii) providing demonstrations in the target language (*in-language demonstrations;* Fu et al., 2022; Qin et al., 2023; Huang et al., 2023; Zhang et al., 2024b). Both strategies have critical shortcomings: (i) may suffer from information loss in translation due to nuanced language gap (Zhang et al., 2023;

Poelman and de Lhoneux, 2024) or the unavailability of high-quality translation systems for extremely low-resource languages (LRLs), whereas (ii) may become infeasible due to data scarcity in LRLs. As alternatives, when presenting LLMs with the problems in the target language, English demonstrations (Fig. 1a) lead to poor performance on LRLs, whereas demonstrations in multiple high-resource languages (HRLs; Fig. 1b) can be more effective, even when there are little alphabetical overlap between the demonstration and target languages (Shi et al., 2023); however, the underlying reasons on why it works remain unclear.

In this work, we systematically analyze multilingual ICL through a set of controlled experiments. Each test question is paired with a set of semantically equivalent demonstrations, while the demonstration languages vary according to different ICL modes (§ 3). We compare the performance differences across four ICL modes (§§ 4.1 and 4.2): English, individual-HRL, multilingual (i.e., mixed HRLs), and in-language demonstrations (Fig. 2). To disentangle the impact of demonstration language from other confounding factors (e.g., interactions between demonstration languages and in-domain demonstrations), we conduct additional control experiments by adding irrelevant sentences in various languages into English-only in-domain demonstrations (§ 4.3). We find that

- In-context demonstrations in HRLs, especially in languages with non-Latin writing system such as Chinese and Japanese, can more effectively transfer knowledge compared to English ICL mode, leading to performance improvement on answering questions in all languages, especially in LRLs. This finding is generalizable enough across different domains and various LLMs.
- Demonstrations in mixed HRLs is more robust and effective compared to that in a single HRL, in terms of average accuracy boosting on different tasks. This strategy is favored.
- Surprisingly, simply introducing another non-English language (not necessarily in the demonstration) in the prompt could lead to performance improvement, albeit the improvement is not as significant as the aforementioned strategies.

2 Background: Multilingual ICL

In this section, we review the basic approaches of ICL with instruction-tuned LLMs (§ 2.1) and introduce the multilingual prompting modes (§ 2.2) that we evaluate in this work.

2.1 ICL for Instruction-Tuned LLM

Instruction-tuned LLMs (Ouyang et al., 2022; Mishra et al., 2022; Wang et al., 2022; Wei et al., 2022a) generally possess the capability to follow task instructions (i.e., *system prompt*), which are usually coupled with ICL to fully elicit their capability (Wei et al., 2022b, *inter alia*). Formally, denote a training set by $\mathcal{D}_{\text{train}} = \{(q_i, a_i)\}_{i=1}^{M}$ and a test set $\mathcal{D}_{\text{test}} = \{(q_j, a_j)\}_{j=1}^{N}$ in the same domain, where q_i is a task question (as model *input*). An ICL prompt for a test question $q_{\text{test}} \in \mathcal{D}_{\text{test}}$ has three core components: (1) a system prompt I_{sys} that describes the task and specifies the expected output format, (2) K sample input-output pairs (K-shot) from the training set $\{(q_k, a_k)\}_{k=1}^{K} \sim \mathcal{D}_{\text{train}}$ that provide in-context demonstrations, and (3) a verbalizer V mapping each ground truth label a_i to a textual representation, which may also include reasoning steps (i.e., chains of thoughts, or CoT in short; Wei et al., 2022b). In summary, an ICL prompt for q_{test} can be written as:

$$\begin{aligned}\text{prompt}_{q_{\text{test}}} = I_{\text{sys}} \circ q_1 \circ V(a_1) \circ q_2 \circ V(a_2) \\ \circ \cdots \circ q_K \circ V(a_K) \circ q_{\text{test}}, \end{aligned} \quad (1)$$

where $\circ$ is the string concatenation operator with a special end-of-turn (`EOT`) token as the delimiter. The LLM with parameters $\boldsymbol{\theta}$, denoted as $p_{\boldsymbol{\theta}}$, then generates the response $\hat{a}_{\text{test}}$ given $\text{prompt}_{q_{\text{test}}}$: $\hat{a}_{\text{test}} \sim p_{\boldsymbol{\theta}}\left(\text{prompt}_{q_{\text{test}}}\right)$.

2.2 Multilingual Prompting Modes

We extend our notations as follows to adapt to the multilingual settings. A training set with L languages is denoted by $\mathcal{D}_{\text{train}} = \left\{\mathcal{D}_{\text{train}}^{\text{lang}_1}, \ldots, \mathcal{D}_{\text{train}}^{\text{lang}_L}\right\}$, where the split $\mathcal{D}_{\text{train}}^{\text{lang}_\ell}$ consists of M examples for any $\ell \in \{1, \ldots, L\}$. The same applies to the test dataset $\mathcal{D}_{\text{test}}$, with each language-specific split consisting of N examples. Without further specification, we assume that the training examples at the same index are semantically equivalent across languages.

The ground-truth labels a_i in quantitative LLM benchmarks (Ponti et al., 2020; Cobbe et al., 2021, *inter alia*) are typically language-agnostic (such as numbers) or represented in a single word (such as Yes/No). In such cases, the verbalizer is an identity. For answers requiring reasoning steps, $V(a_i)$ is CoT in English, as there has been strong evidence

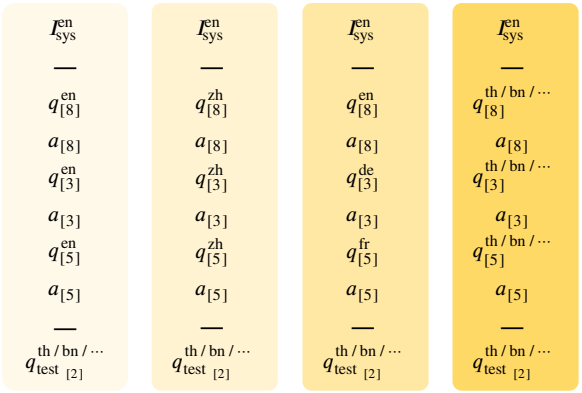


Figure 2: Illustration of ICL modes by Eq. (1). Assume $K = 3$ and $M = 10$. For the second datapoint of the test set (regardless of its language split, e.g., q_{test} could be in Thai, Bengali, etc.), we first randomly generate $K = 3$ indices from $\{1, \cdots, 10\}$, say $\{8, 3, 5\}$. Next, we determine the languages of the $K = 3$ demonstrations. For modes (a), (b), and (d), the language is uniformly specified. For mode (c), we randomly select $K = 3$ languages, say $\{\text{de}, \text{fr}, \text{ja}\}$. Then $\{(8, \text{de}), (3, \text{fr}), (5, \text{ja})\}$ determines each demonstration.

that MLLMs performs better when generating English (Shi et al., 2023; Qin et al., 2023; Huang et al., 2023, *inter alia*). For the same reasons, I_{sys} is always presented in English as well.

Following Ahuja et al. (2023) and Shi et al. (2023), we evaluate MLLMs via several different prompting strategies (*ICL modes*) in this work:

The `English` mode. The K demonstrations are always in English (Figs. 1a and 2a).

The `Monolingual` mode(s). The K demonstrations are always presented in a single non-English high-resource language such as Chinese (Fig. 2b).

The `Multilingual` mode. From a predefined list of high-resources languages $\mathcal{L}_H$, K languages are randomly selected, which, together with the sampled K indices, determine the contents and languages of the K demonstrations (Figs. 1b and 2c).

The `Native` mode. The K demonstrations are in the same language as the test question (Fig. 2d).

3 Experiment Setups

Models. We evaluate state-of-the-art instruction-tuned LLMs with about 8 billion parameters, which have officially claimed multilingual capabilities in model release: Llama3-8B-Instruct, Llama3.1-8B-Instruct (Dubey et al., 2024), Qwen2-7B-Instruct (Yang et al., 2024a), Qwen2.5-7B-Instruct (Yang et al., 2024b), Mistral-NeMo-12B-Instruct (MistralAI, 2024) and Aya-Expanse-8B (Dang et al., 2024). For additional references, we evaluate OpenAI closed-sourced commercial models, including GPT3.5-turbo (OpenAI, 2022) and GPT4o-mini (OpenAI, 2024). Detailed model cards can be found in App. A.1.

Datasets. We evaluate the models using multilingual benchmarks from three distinct domains: (1) MGSM (Shi et al., 2023), a benchmark of 250 grade-school math problems sampled from the English GSM8K (Cobbe et al., 2021) and translated into 10 additional languages by expert native speakers. (2) XCOPA (Ponti et al., 2020), a commonsense reasoning benchmark that extends the COPA dataset (Roemmele et al., 2011) to 11 additional languages.[1] (3) XL-WiC (Raganato et al., 2020), a cross-lingual word-in-context understanding dataset spanning 13 languages, where models are expected to tell whether a polysemous word retains the same meaning in two contexts.

MGSM and XCOPA are *parallel* where each corresponding datapoint across different language splits contains semantically equivalent content, allowing us to minimize semantic confounders in our experimental design. XL-WiC is language-specific and translation-variant thus naturally non-parallel. Dataset properties and examples are in Tabs. 1 and 6. Details of data curation are in App. A.2.

Languages. Languages with large-scale digitized data resources on web are known as *high-resource languages* (HRLs; Bender, 2019), which are exemplified by English, Spanish, Chinese, among others. In contrast, *low-resource languages* (LRL) have scarce accessible data (Costa-jussà et al., 2022). However, a universal standard for dichotomizing languages as either high- or low-resource has not been set (Bender, 2019; Joshi et al., 2020; Hedderich et al., 2021). Moreover, none of the models we evaluate has disclosed the language distributions in their training corpora. As a workaround, we define our preset HRL list as the union of the 20 most frequent languages in Llama2 (Touvron et al., 2023) and PaLM (Chowdhery et al., 2023), and classify languages out of the HRL list as LRLs. Details of preset HRL list can be found in App. A.3.

Prompts. Following Shi et al. (2023), we use $K = 6$ examples for demonstration for any test question. For each multilingual dataset (Tab. 1), we first sample N index lists of length $K = 6$ all at once, where the index range is $\{1, 2, \cdots, M\}$. We allocate the i-th index list to the set of test questions

[1] In this work, we merge the English COPA and XCOPA datasets together, which we still refer to as XCOPA.

Dataset Domain *Datapoint Example*	Expected Output	#Languages (#HRL + #LRL)	Language Split Size M/N — Training/Test	En Avg Word Count$_{\pm \text{std}}$	Parallel
MGSM Mathematical Reasoning *See Fig. 1 for examples.*	Numerals	11 (7 + 4)	8/250	$46.26_{\pm 18.29}$	✔
XCOPA Commonsense Reasoning *Premise: The man turned on the faucet.* *What happened as a RESULT?* *Hypothesis 1: The toilet filled with water.* *Hypothesis 2: Water flowed from the spout.* *Answer: 2.*	"1" / "2"	12 (5 + 7)	100/500	$26.59_{\pm 3.41}$	✔
XL-WiC Word Disambiguation *Sentence 1: What did you *get* at the toy store?* *Sentence 2: She didn't *get* his name when they met the first time.* *Question: Is the word "get" (marked with *) used in the same way in both sentences above?* *Answer: No.*	"Yes" / "No"	13 (9 + 4)	98/390	$35.65_{\pm 5.36}$	✖

Table 1: Dataset properties and examples. Each language split (for both training and test) is of the same size. In-context demonstrations are randomly drawn from the training dataset. Data source and languages are documented in Tab. 6 in App. A.2. Texts in blue represent *interfaces* acting like reserved words in programming languages (Poelman and de Lhoneux, 2024).

$q_{\text{test}_i} = \left\{ q_{\text{test}_i}^{\text{lang}_1}, q_{\text{test}_i}^{\text{lang}_2}, \cdots, q_{\text{test}_i}^{\text{lang}_L} \right\}$ for the same index i across all L language splits. The training-set index list, together with the specified languages,[2] jointly determines the content and language of the demonstration for each testing example (Fig. 2). This approach both ensures linguistic diversity for multilingual prompting and, whenever applicable, mitigates confounding factors that come with semantic inconsistency across examples. All *interface* words (see Tab. 1) are in the same language as the examples rather than in English.

Inference and metrics. Throughout this work, we use greedy decoding for inference, selecting the token with the highest probability at each step. For MGSM in need of CoT, we set the maximum token length to 500; for XCOPA and XL-WiC, we set it to 10, as we expect the answers to be short. We use exact match accuracy as our evaluation metric: for MGSM, we extract the last numeral in the response. For XCOPA and XL-WiC, we extract label (*expected output*) in the response (Tab. 1).

4 ICL Mode Evaluation

4.1 `Multilingual` Prompts Surpass `English`

Results. We first compare the 6-shot performance with `English`, `Multilingual` and `Native` ICL modes on 6 open-sourced MLLMs and 2 commercial OpenAI models (Fig. 3), with Tab. 2 presenting the detailed performance of three selected MLLMs across various LRLs. Overall, `Multilingual` mode outperforms `English` mode, both for individual LRLs and on average. In 18 out of 24 cases (Fig. 3), `Multilingual` mode achieves higher accuracy than `English` one. This phenomenon is evident even for GPT4o-mini, one of the currently strongest LLMs (Chiang et al., 2024), and for HRLs as well (see Tabs. 11 to 13 in App. B.1 for HRL accuracies). Extending the results of Shi et al. (2023) that `Multilingual` mode generally outperforms `English` mode for PaLM (Chowdhery et al., 2023) and Codex (Chen et al., 2021), our results confirm this trend is a general phenomenon across various MLLMs and datasets.

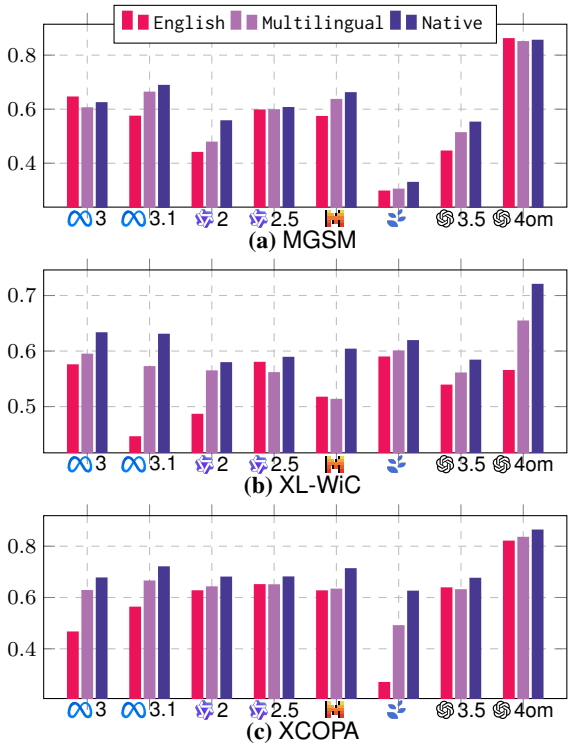


Figure 3: Average accuracies of LRLs across three ICL modes on our evaluated 3 datasets and 7 MLLMs. Raw accuracies of all language splits are in Tabs. 11 to 13 in App. B.1. For simplicity, on the x-axis, only the model logos are labeled – 3: Llama3-8B-Instruct; 3.1: Llama3.1-8B-Instruct; 2: Qwen2-7B-Instruct; 2.5: Qwen2.5-7B-Instruct; : Mistral-NeMo-12B-Instruct; : Aya-Expanse-8b; 3.5: GPT3.5-turbo; 4om: GPT4o-mini.

Outstanding performance of the `Native` mode

[2] For the `Multilingual` mode, we apply the same sampling procedure to generate N HRL code lists of length $K = 6$, drawing from the available HRLs in the dataset.

Acc (%)$_{\Delta\uparrow\downarrow}$	MGSM					XL-WiC					XCOPA
	bn	sw	te	th	LRL Avg	bg	et	fa	hr	LRL Avg	LRL Avg
Llama3.1-8B-Instruct											
English	52.40	67.20	39.60	69.20	57.10	51.54	44.62	29.74	51.79	44.42	55.91
Multilingual	68.00	68.80	55.60	71.60	$66.00^{***}_{8.90\uparrow}$	57.69	55.13	57.95	56.92	$57.05^{***}_{12.63\uparrow}$	$66.11^{***}_{10.20\uparrow}$
Native	67.20	72.40	58.00	76.40	$68.50^{***}_{11.40\uparrow}$	61.79	62.05	62.31	57.18	$62.88^{***}_{18.46\uparrow}$	$71.63^{***}_{15.72\uparrow}$
Qwen2-7B-Instruct											
English	57.20	20.80	23.20	73.60	43.70	28.21	56.92	63.33	54.87	48.46	62.29
Multilingual	64.80	28.40	23.60	73.20	$47.50^{**}_{3.80\uparrow}$	53.59	58.46	60.26	54.36	$56.28^{***}_{7.82\uparrow}$	$63.83^{*}_{1.54\uparrow}$
Native	72.00	32.40	40.40	76.80	$55.40^{***}_{11.70\uparrow}$	55.13	59.23	63.08	54.62	$57.76^{***}_{9.30\uparrow}$	$67.63^{***}_{5.34\uparrow}$
GPT3.5-turbo											
English	39.60	63.60	12.80	60.80	44.20	54.36	54.62	54.10	51.79	53.72	63.43
Multilingual	54.40	68.00	24.40	57.20	$51.00^{***}_{6.80\uparrow}$	52.82	60.00	54.36	56.41	$55.90^{**}_{2.18\uparrow}$	$62.71_{0.72\downarrow}$
Native	57.20	73.60	30.00	58.80	$54.90^{***}_{10.70\uparrow}$	54.62	59.49	58.46	60.26	$58.21^{***}_{4.49\uparrow}$	$67.17^{***}_{3.74\uparrow}$

Table 2: Accuracies on LRLs of English, Multilingual and Native modes across 3 MLLMs of 3 datasets. Please refer to Tab. 9 for language code-to-name mapping. Avg represents the average accuracy of the LRLs. Subscript indicate the performance increase↑ (or decrease↓) of Multilingual and Native compared to English. Superscripts are significance levels (in terms of p-value) of the same comparison — *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$. Raw evaluation accuracies and hypothesis test results for all MLLMs and all languages are in Tabs. 11 to 13 and Tabs. 14 to 16 in App. B.1, respectively.

and the practical unfeasibility. Admittedly, in 22 out of 24 comparisons, Native mode outperforms Multilingual mode (Fig. 3), which aligns with the machine-learning intuition that in-domain data, in terms of both genre and language, are more promising for model performance (Liu et al., 2024). However, domain-specific datasets for LRLs are often difficult to obtain due to the scarcity of native speakers or professional translators (Costa-jussà et al., 2022; NLLB-Team, 2024); therefore, in practice, it is usually challenging to provide high-quality demonstrations in the same language and domain as the test question. In contrast, annotations makes the HRL-Multilingual mode more feasible in many scenarios.

Hypothesis Tests. To verify whether the improvement is statistically significant, we conduct McNemar's test (McNemar, 1947)—the null hypothesis means no significant accuracy difference between the baseline (English) and the compared mode. Let b denote the number of cases where the baseline is correct while the compared mode is incorrect, c denotte the number of cases where the baseline mode is incorrect while the compared mode is correct. We calculate the corrected version (Edwards, 1948) of the McNemar's statistic:

$$\chi^2 = \frac{(|b-c|-1)^2}{b+c}, \qquad (2)$$

which has a chi-squared distribution with one degree of freedom. Significant χ^2-test results provide strong evidence to reject the null hypothesis of no accuracy improvement. Our results results (Tab. 2 and Tabs. 14 to 16 in App. B.1) indicate

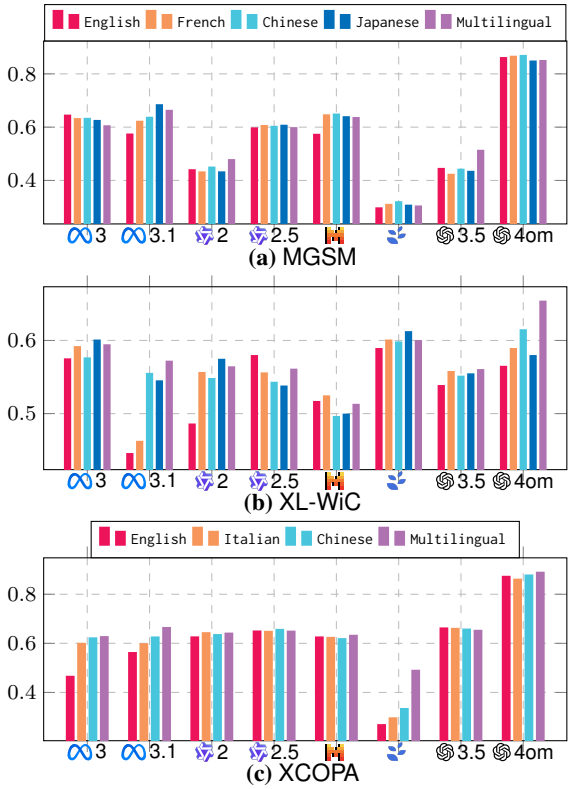


Figure 4: Monolingual modes vs Multilingual on average accuracies of LRLs. The x-axis is the same as in Fig. 3. Raw evaluation accuracies are in Tabs. 11 to 13 in App. B.1.

that both Multilingual and Native modes significantly outperform the English mode.

4.2 Ablation Study: Non-English Monolingual Prompts Are Effective

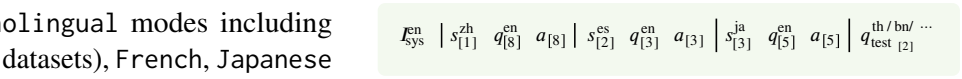
With the success of the Multilingual mode, we investigate whether the improvement comes from the introduction of multiple languages or simply from a single non-English HRL. Specifically, we

compare several Monolingual modes including Chinese (for all three datasets), French, Japanese (both for MGSM and XL-WiC) and Italian (for XCOPA). We select French and Italian because they are both European languages and thus share considerable subword overlap with English; in contrast, Chinese and Japanese exhibit little subword overlap with Latin-script languages, but there is a substantial overlap between them two due to their shared use of Chinese characters (or *kanji*). This language selection allows us to analyze simultaneously the impact of the writing system (or *subword overlap*) on ICL performance.

Results. All HRL-Monolingual modes outperform English in a considerable number of comparisons (Fig. 4). This finding also holds for HRL evaluations (see Tabs. 11 to 13 in App. B.1 for raw accuracies of each language). Among all Monolingual modes, Chinese performs the best, matching Multilingual mode with 17 out of 21 comparisons when accuracy surpasses that of English. Japanese also frequently outperforms English. Extending the findings of Turc et al. (2021) that non-English languages are more effective than English in pretraining and fine-tuning based cross-lingual transfer, our results suggest that non-English languages, particularly those with non-Latin scripts, may be more effective under the prompting scheme as well.

However, the Multilingual mode exhibits stronger robustness, outperforming Chinese in 14 out of 21 LRL cases. Same trends applies to HRLs. The results of the hypothesis test further confirm the robustness: for both LRL and HRL splits, the Multilingual mode exhibits the highest number of significant results relative to other Monolingual modes (Tabs. 14 to 16 in App. B.1). Intuitively, we hypothesize that Multilingual mode functions like an "average" of individual HRL-Monolingual modes, making it most robust, and thus it outperforms English most frequently and achieves the highest overall average accuracy.

Following Tang et al. (2024), we further identify ICL-mode-specific neurons and find that the neurons activated by Multilingual overlap most with those activated by Native among other modes. This further explains why Multilingual could achieve performance comparable to Native. See App. C for details.



English ICL Mode + Multilingual Context-Irrelevant Sentences (English + CIS-Multi)

Figure 5: Prepending multilingual CIS (CIS-Multi) $\{s_i^{\text{lang}}\}_{i=1}^{K} \sim \mathcal{S}^{\text{lang}}$ to demonstrations $\{(q_i^{\text{en}}, a_i)\}_{i=1}^{K} \sim \mathcal{D}_{\text{train}}^{\text{en}}$ of English ICL template illustrated in Fig. 2a.

4.3 Ablation Study: Merely Introducing New Language(s) Enhances ICL Performance

After showing that including non-English in the prompts can improve ICL performance, a natural follow-up question arises: does the gain come from the mere presence of non-English languages, or the interaction between the target language and the in-topic examples? To distinguish these two setups, we prepend a *context-irrelevant sentence* (CIS) s^{lang} before each ICL demonstration, which is unrelated to the current domain and can be in any language. Analogous to the ICL modes introduced in § 2.2, CIS resembles the construction of those modes with the same sampling strategy (§ 3). For example, based on the English mode, we could prepend a set of multilingual CIS, which augments Fig. 2a into Fig. 5. We denote such setting by "English + CIS-Multi". This naming convention applies to other settings accordingly.

We use sentences from FLORES-101 (Goyal et al., 2022) as the source of our CIS, which provides parallel Wikipedia sentences in multiple languages, a fairly distant genre to all evaluation datasets. We filter sentence-parallel sets with English word counts ranging from 10 to 15 as our sampling pool $\mathcal{S}^{\text{lang}}$, a small range compared to target datasets (Tab. 1), to mitigate the risk of introducing too much noise. Details of FLORES-101 can be found at App. A.2.

Results and analysis. We perform hypothesis testing as in § 4.1 to compare different CIS settings with English + CIS-En (Tab. 3)—English + CIS-En exhibit a small drop compared to English only, indicating that our filtration effectively controls the negative impact of noise to a tolerable level. We find that introducing a single non-English language generally improves ICL performance in most cases $\left(\frac{44}{54} \approx 82\%\right)$; however, the improvement is only statistically significant in $\frac{20}{44} \approx 45\%$ cases. This reveals that simply introducing a language can lead to a modest improvement in MLLM performance, but it is more pronounced when in-topic demonstrations in another language (Monolingual modes) are incorporated. More hy-

pothesis test results for both LRL and HRL splits can be found in Tabs. 20 to 22 in App. B.2.

Introducing multiple languages (CIS-Multi, Fig. 5) is slightly more promising than CIS in a single language, with $\frac{16}{18} \approx 89\%$ of cases showing improvement, of which $\frac{9}{16} \approx 56\%$ are significant. We further conduct experiments by prepending multilingual CIS to the Multilingual mode (Multilingual + CIS-Multi, Tab. 3). The performance of Multilingual + CIS-Multi is not significantly lower than that of English + CIS-Multi; in more than half cases, it significantly outperforms English + CIS-Multi. This concludes that the significant improvement from English mode to Multilingual mode is attributed to the incorporation of multiple languages with in-topic demonstrations.

4.4 Translation-Based Performance

Mirroring the translation-training (Hu et al., 2020, *inter alia*) setup, existing work suggest that translating from LRLs into English and prompting with the translation results may yield better results (Ahuja et al., 2023, *inter alia*). While translation is not the main focus of our work, we conduct experiment to compare the performance of translation-based strategies for reference.

Strategies. We test two translation strategies for baseline comparison. (1) Transl-Lang→En: Translating test questions in other languages in the English ICL mode (Fig. 2a) into English. (2) Transl-En→Lang: Translating demonstrations in English ICL mode (Fig. 2a) into the source language of the current test question, which mirrors the Native mode (Fig. 2d). We use the Google Cloud Translation API for translation.[3]

Analysis. For LRLs, Transl-Lang→En sometimes outperform the Native mode, while Transl-En→Lang performs comparably to the Multilingual mode, but falls short of the Native mode performance (Tab. 4). These results resonate with the phenomena that the translation quality of LRL→En is generally higher than that of the reversed direction (Fan et al., 2021; Goyal et al., 2022; Costa-jussà et al., 2022).

For HRLs, however, Transl-Lang→En underperforms to Native and, sometimes, even Multilingual (e.g., on MGSM), suggestting that if a language is sufficiently well-trained, generating responses directly in that language is more effec-

[3] https://cloud.google.com/translate/

LRL Avg$_{\Delta\uparrow\downarrow}$ (%)	MGSM	XL-WiC	XCOPA
Llama3-8B-Instruct			
English	64.20	57.37	46.23
English + CIS-En	61.00	56.73	48.37
English + CIS-Fr	$61.60_{0.30\uparrow}$	$57.50_{0.77\uparrow}$	$58.49^{***}_{10.12\uparrow}$
English + CIS-Ja	$61.30_{0.30\uparrow}$	$58.14_{1.41\uparrow}$	$58.69^{***}_{10.32\uparrow}$
English + CIS-Zh	$59.30_{1.70\downarrow}$	$58.27_{1.54\uparrow}$	$58.03^{***}_{9.66\uparrow}$
English + CIS-Multi	$60.50_{0.50\downarrow}$	$57.82_{1.09\uparrow}$	$61.14^{***}_{12.77\uparrow}$
Multilingual + CIS-Multi	$60.10_{0.40\downarrow}$	$58.33_{0.51\uparrow}$	$61.54_{0.40\uparrow}$
Llama3.1-8B-Instruct			
English	57.10	44.42	55.91
English + CIS-En	55.90	47.88	55.46
English + CIS-Fr	$52.10^{*}_{3.80\downarrow}$	$52.82^{***}_{4.94\uparrow}$	$59.40^{***}_{3.94\uparrow}$
English + CIS-Ja	$58.80_{2.90\uparrow}$	$55.96^{***}_{8.08\uparrow}$	$59.86^{***}_{4.40\uparrow}$
English + CIS-Zh	$55.00_{0.90\downarrow}$	$54.68^{***}_{6.80\uparrow}$	$64.66^{***}_{9.20\uparrow}$
English + CIS-Multi	$62.50^{***}_{6.60\uparrow}$	$56.03^{***}_{8.15\uparrow}$	$64.74^{***}_{9.28\uparrow}$
Multilingual + CIS-Multi	$68.60^{***}_{6.10\uparrow}$	$57.24_{1.21\uparrow}$	$66.20^{*}_{1.46\uparrow}$
Qwen2-7B-Instruct			
English	43.70	48.46	62.29
English + CIS-En	43.00	50.90	62.31
English + CIS-Fr	$43.50_{0.50\uparrow}$	$53.65^{***}_{2.75\uparrow}$	$62.31_{0.00-}$
English + CIS-Ja	$43.80_{0.80\uparrow}$	$56.22^{**}_{5.32\uparrow}$	$63.09_{0.78\uparrow}$
English + CIS-Zh	$42.60_{0.40\downarrow}$	$56.79^{***}_{5.89\uparrow}$	$62.49_{0.18\uparrow}$
English + CIS-Multi	$42.70_{0.30\downarrow}$	$54.94^{***}_{4.04\uparrow}$	$62.51_{0.20\uparrow}$
Multilingual + CIS-Multi	$47.30^{***}_{4.70\uparrow}$	$55.83_{0.89\uparrow}$	$63.51_{1.00\uparrow}$
Qwen2.5-7B-Instruct			
English	59.40	57.82	64.69
English + CIS-En	59.40	59.04	64.20
English + CIS-Fr	$59.40_{0.00-}$	$59.04_{0.00-}$	$64.11_{0.09\downarrow}$
English + CIS-Ja	$60.10_{0.70\uparrow}$	$59.36_{0.32\uparrow}$	$64.20_{0.00-}$
English + CIS-Zh	$60.90_{1.50\uparrow}$	$59.23_{0.19\uparrow}$	$65.20^{*}_{1.00\uparrow}$
English + CIS-Multi	$59.50_{0.10\uparrow}$	$59.36_{0.32\uparrow}$	$65.06_{0.86\uparrow}$
Multilingual + CIS-Multi	$59.20_{0.30\downarrow}$	$56.79^{*}_{2.57\downarrow}$	$64.14_{0.92\downarrow}$
NeMo-12B-Instruct			
English	57.00	51.54	62.26
English + CIS-En	60.70	49.62	61.00
English + CIS-Fr	$61.40_{0.70\uparrow}$	$50.58^{*}_{0.96\uparrow}$	$61.23_{0.23\uparrow}$
English + CIS-Ja	$60.20_{0.50\downarrow}$	$49.87_{0.25\uparrow}$	$61.80_{0.80\uparrow}$
English + CIS-Zh	$60.50_{0.20\downarrow}$	$50.06_{0.44\uparrow}$	$61.14_{0.14\uparrow}$
English + CIS-Multi	$64.90^{***}_{4.20\uparrow}$	$50.19_{0.57\uparrow}$	$62.23^{*}_{1.23\uparrow}$
Multilingual + CIS-Multi	$62.90_{2.00\downarrow}$	$52.76^{**}_{2.57\uparrow}$	$61.97_{0.26\downarrow}$
Aya-Expanse-8B			
English	29.40	58.78	26.54
English + CIS-En	27.80	57.82	23.20
English + CIS-Fr	$28.70_{0.90\uparrow}$	$61.54^{***}_{3.72\uparrow}$	$28.71^{***}_{5.51\uparrow}$
English + CIS-Ja	$29.30_{1.50\uparrow}$	$61.03^{**}_{3.21\uparrow}$	$33.06^{***}_{9.86\uparrow}$
English + CIS-Zh	$28.60_{0.80\uparrow}$	$60.58^{**}_{2.76\uparrow}$	$26.94^{***}_{3.74\uparrow}$
English + CIS-Multi	$27.90_{0.10\uparrow}$	$62.24^{***}_{4.42\uparrow}$	$33.60^{***}_{10.40\uparrow}$
Multilingual + CIS-Multi	$31.50^{**}_{3.60\uparrow}$	$61.09_{1.15\downarrow}$	$45.91^{***}_{12.31\uparrow}$

Table 3: Average accuracies on LRLs after prepending English, monolingual or multilingual CIS to the original English mode. Subscripts denote the accuracy delta between the current value and that of English + CIS-En. Except for Multilingual + CIS-Multi, subscripts represent the difference of the current value and English + CIS-Multi. The asterisk superscript indicates the significance level, which we compare in the same way as the accuracy delta. Raw evaluation accuracies for all languages (both LRLs and HRLs) are in Tabs. 17 to 19 in App. B.2. Raw hypothesis test results for CIS mode comparisons are in Tabs. 20 to 22 in App. B.2.

Avg Acc (%)	MGSM		XCOPA	
	LRL	HRL	LRL	HRL
Llama3.1-8B-Instruct				
Multilingual	66.00	79.20	66.11	89.64
Native	68.50	79.43	71.63	90.80
Transl-Lang→En	60.00	74.80	76.74	89.68
Transl-En→Lang	68.60	80.63	70.49	90.04
Qwen2.5-7B-Instruct				
Multilingual	59.50	86.97	64.63	91.84
Native	60.30	87.31	67.69	92.64
Transl-Lang→En	63.40	78.63	80.49	91.52
Transl-En→Lang	59.90	86.97	66.23	92.48
NeMo-12B-Instruct				
Multilingual	63.30	81.09	62.94	88.16
Native	65.80	81.26	70.91	90.28
Transl-Lang→En	61.60	76.00	77.83	89.32
Transl-En→Lang	66.60	82.00	68.46	90.52

Table 4: Average accuracies on MGSM and XCOPA datasets. The comparison includes two translation strategies, the Native mode and our proposed Multilingual mode, evaluated across low- and high-resource language splits. Raw accuracies of individual languages and more models are recorded in Tabs. 11 and 12 in App. B.1.

tive than translating into English before inference. These two findings highlight that MLLMs approach the ideal of being equally capable in HRLs (Liu et al., 2024), but are still undertrained on LRLs, making translation into English a favored strategy.

In agreement with Poelman and de Lhoneux (2024), we would like to note that even if the task performance of translation-based strategies are the best, the ultimate goal of multilingualism is not just about optimizing task-specific performances. A universal language model should be able to understand and generate text in all languages, instead of relying on specific language(s) as an intermediary. On the other hand, due to the loss of semantic nuances, grammatical structures and cultural context, translation-based strategies may not be the best choice for tasks heavily reliant on language-specific nuances (Liu et al., 2024).

5 Related Work

Prompt engineering. Instruction tuning aligns LLMs more closely with human instructions (Ouyang et al., 2022; Mishra et al., 2022; Wei et al., 2022a; Askell et al., 2021; Wang et al., 2022, 2023). Concurrently, numerous prompting strategies have been developed (Liu et al., 2023) and shown to consistently enhance the performance of instruction-tuned LLMs, such as in-context learning (Brown et al., 2020; Min et al., 2022) and chain-of-thought (Wei et al., 2022b; Kojima et al., 2022). These prompting strategies are proven effective in multilingual tasks as well (Winata et al., 2021; Lin et al., 2022; Shi et al., 2023).

Multilingual ICL. For languages of templates, demonstration and sample question in native language is conventionally inserted into a predefined English template (Lin et al., 2022; Fu et al., 2022; Qin et al., 2023; Huang et al., 2023; Ahuja et al., 2023; Zhang et al., 2024b). Poelman and de Lhoneux (2024) critiques this widespread misuse of English as the *interface* language. Qin et al. (2023); Huang et al. (2023); Zhang et al. (2024b) guide models to "think" and generate CoT in English, regardless of the input language, leading to improved performance for generation tasks compared to "thinking" in other language(s). Sclar et al. (2024); Zhang et al. (2024a) highlight that models are sensitive to those templates. For languages of demonstrations and test questions, Shi et al. (2023); Ahuja et al. (2023) conclude that in-language demonstrations outperform English demonstrations. Etxaniz et al. (2024); Liu et al. (2024) suggest translating questions from LRLs into English can improve performance.

6 Conclusion and Discussion

This work systematically analyzes multiple ICL strategies for MLLMs, and confirms that the presence of multiple languages is an effective strategy across multiple MLLMs. This improvement is partially due to the inclusion of non-English languages in the prompting, and partially due to the in-topic demonstrations in non-English languages, which together strengthen the models' cross-lingual transfer capabilities, particularly the capability to process LRLs. Our work echoes with Turc et al. (2021)—who suggest that HRLs other than English excel in the pretraining-finetuning framework—in the in-context learning framework, highlighting the importance of language inclusivity.

We are in agreement with Costa-jussà et al. (2022) and Liu et al. (2024) that an ideal language-universal LLM should be equally capable in all languages. Beyond this belief, we found that non-English languages may better elicit the potential of MLLMs. Although these observations remain in using HRLs for LRL processing, our results strongly support the call for greater research investment in enhancing MLLM capabilities for a broader range of languages.

Limitations

This paper treats multilingual LLMs as black-box models, drawing the findings and conclusions based solely on their input-output behavior. Hence we have not interpreted the internal mechanism how multilinguality could affect MLLM's "thinking" process and its manifested performance. We have briefly touched the impact of demonstrations in different languages on the MLLM performance. However, we do not conduct a thorough empirical analysis to identify which specific linguistic characteristics (e.g., writing systems, grammatical structures, or linguistic relatedness) contribute to the observed performance differences.

Reproducibility

Our code is available at `https://anonymous.4open.science/r/multilingual_icl-AF37/`.

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A Experiment Setup

A.1 Model

All model checkpoints we use and their properties are listed in Tab. 5.

A.2 Dataset

After preprocessing, datapoints for each language split are stored in a single JSON file. Tab. 6 summarizes the supported languages for each dataset and the sources from which they are obtained.

MGSM The original dataset consists of parallel datapoints across all language splits and training/test splits of the same size. Example datapoint and the Chat Template for few-shot demonstrations can be found in Fig. 6.

XCOPA The 100 datapoints in the training split of XCOPA are parallel to the last 100 datapoints in the English COPA development split. Therefore, we exclude the first 400 datapoints from the development split of English COPA. The test splits of both datasets are parallel and contain the same number of datapoints. We then merge both into our XCOPA dataset. In XCOPA, there are two types of questions: "cause" and "effect", each corresponding to a distinct template, as shown in Figs. 7a and 7b.


```
{
  "question": "Question: Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?",
  "answer": "Step-by-Step Answer: Leah had 32 chocolates and Leah's sister had 42. That means there were originally 32 + 42 = 74 chocolates. 35 have been eaten. So in total they still have 74 - 35 = 39 chocolates. The answer is 39.",
  "answer_number": 39,
  "language": "en",
},
```


ICL Q Question: Leah had 32 chocolates and her sister had 42. If they ate 35, how many pieces do they have left in total?

ICL A Step-by-Step Answer: Leah had 32 chocolates and Leah's sister had 42. That means there were originally 32 + 42 = 74 chocolates. 35 have been eaten. So in total they still have 74 - 35 = 39 chocolates. The answer is 39.

Figure 6: An example of an English datapoint from MGSM training set. When calling Chat Template API, `user` role message is the "question" value, while `assistant` role message is the "answer" value. Note that in the test set, the answer is null without exemplar CoT response. The correct numerical answer is stored in "answer_number".


```
{
  "premise": "My eyes became red and puffy.",
  "choice1": "I was sobbing.",
  "choice2": "I was laughing.",
  "question": "cause",
  "label": 1,
  "language": "en"
},
```


ICL Q Premise: My eyes became red and puffy.
What was the CAUSE of this?
Hypothesis 1: I was sobbing.
Hypothesis 2: I was laughing.

ICL A 1.

(a) An example of "cause" datapoint.


```
{
  "premise": "The man turned on the faucet.",
  "choice1": "The toilet filled with water.",
  "choice2": "Water flowed from the spout.",
  "question": "effect",
  "label": 2,
  "language": "en",
}
```


ICL Q Premise: The man turned on the faucet.
What happened as a RESULT?
Hypothesis 1: The toilet filled with water.
Hypothesis 2: Water flowed from the spout.

ICL A 2.

(b) An example of "effect" datapoint.

Figure 7: Examples of English datapoints from XCOPA training set. First, based on whether "question" is "cause" or "effect", we fill the "premise", "choice1", and "choice2" values into one of the two predefined templates. The template's language is changeable as per the language split of the datapoint. Then we call the Chat Template API, `user` role message is the filled template, while `assistant` role message is the "label" value.

XL-WiC This benchmark is designed to determine whether a specific word in a given language has the same meaning in two different sentences. As a result, the dataset is inherently non-parallel. Among all language splits, Estonian (et) contains the fewest datapoints, with 98 in the training split and 390 in the test split. For all other languages, we randomly subsample to match the size of the Estonian split to satisfy the demonstration sampling requirements outlined in §2.2. To leverage the attention mechanism of transformers (Vaswani et al., 2017), we add asterisks around the target word in both sentences to indicate that the LLM needs to disambiguate the meaning of that specific word. An example datapoint is shown in Fig. 8.

COMBINED Identifying specific neurons depends on the nature of the input corpus. Since language is inherently conjugate with the task, and our focus is on language-specific neurons rather

Model Name	Scale	Instruct?	Open-Source?	Checkpoint
Llama3-8B-Instruct	8B	✔	✔	meta-llama/Meta-Llama-3-8B-Instruct
Llama3.1-8B-Instruct	8B	✔	✔	meta-llama/Meta-Llama-3.1-8B-Instruct
Qwen2-7B-Instruct	7B	✔	✔	Qwen/Qwen2-7B-Instruct
Qwen2.5-7B-Instruct	7B	✔	✔	Qwen/Qwen2.5-7B-Instruct
NeMo-12B-Instruct	12B	✔	✔	mistralai/Mistral-Nemo-Instruct-2407
Aya-Expanse-8B	8B	✔	✔	CohereForAI/aya-expanse-8b
GPT3.5-turbo	NA	✔	✖	gpt-3.5-turbo-0125
GPT4o-mini	NA	✔	✖	gpt-4o-mini-2024-07-18

Table 5: Model details. Checkpoints are either from Hugging Face or OpenAI API.

Dataset	HRL	LRL	Source
MGSM	de, en, es, fr, ja, ru, zh	bn, sw, te, th	juletxara/mgsm
XCOPA	en, id, it, tr, zh	et, ht, qu, sw, ta, th, vi	English COPA & cambridgeltl/xcopa
XL-WiC	da, de, en, fr, it, ja, ko, nl, zh	bg, et, fa, hr	pilehvar.github.io/xlwic/

Table 6: Additional information for the three datasets we evaluate. The correspondence between language codes and names can be found in Tab. 9. "Source" indicates where to download the dataset. "En Avg Word Count" represents the average word count and standard deviation of the demonstration questions of the English split.


```
{
  "target_word": "get",
  "example_1": "What did you *get* at the toy store?",
  "example_2": "She didn't *get* his name when they
met the first time.",
  "label": 0,
  "language": "en",
},
```


ICL Q
Sentence 1: What did you *get* at the toy store?
Sentence 2: She didn't *get* his name when they met the first time.
Question: Is the word "get" (marked with *) used in the same way in both sentences above?

ICL A No.

Figure 8: An example of English datapoint from XL-WiC training set. We first fill the "example_1", "example_2", and "target_word" values into the predefined templates. Asterisks * are surrounded around "target_word" to draw the LLM's attention. The template's language is changeable as per the language split of the datapoint. Then we call the Chat Template API, `user` role message is the filled template, while `assistant` role message is "Yes" or "No" ("label" is 1 or 0).

than task-specific neurons, it is necessary to input all three datasets into the LLM to eliminate the confounding factor of the task domain. To balance the three datasets, we subsample their test splits to only 250 datapoints each. To balance the number of language splits across datasets, we excluded two HRL splits, Korean (ko) and Dutch (nl), from the XL-WiC dataset. This ensures that all three (sub-)datasets have 11 languages for combination. Additionally, for MGSM, we limit the answers to only include the final numeric result without the CoT reasoning. This approach ensures that the total number of datapoints and the overall token count are roughly the same across the original three datasets.

FLORES-101 This machine translation benchmark comprises 3,001 sentences extracted from English Wikipedia, spanning diverse topics and domains. These sentences were translated into 101 languages by professional translators via a carefully controlled process. The Wikipedia domain is largely unrelated to the domains of the three datasets we evaluate (math, commonsense reasoning, and word disambiguation). Therefore, we choose FLORES-101 as our source pool of irrelevant sentences. Note that in this benchmark, each datapoint carries the same semantic meaning across all 101 language splits. We do not want irrelevant sentences to affect the LLM's understanding of the original task excessively, thus we select sentences with word counts between 10 and 15 in the English split, introducing limited noise. CIS are drawn form the filtered FLORES-101 dataset. An example is provided in Fig. 9.

A.3 Language

A.3.1 High-Resource Language List

To the best of our knowledge, we find two multilingual LLMs—Llama2 (Touvron et al., 2023) and PaLM (Chowdhery et al., 2023)—that publicly report the language distribution used during pretraining. The top 20 languages and their percentages for each model are listed in Tab. 7 and Tab. 8, respectively. We take the union of these languages to form what we consider a *high-resource language list* (in terms of the richness in the LLM pretraining

Code	Language	Percentage
en	English	89.70%
de	German	0.17%
fr	French	0.16%
sv	Swedish	0.15%
zh	Chinese	0.13%
es	Spanish	0.13%
ru	Russian	0.13%
nl	Dutch	0.12%
it	Italian	0.11%
ja	Japanese	0.10%
pl	Polish	0.09%
pt	Portuguese	0.09%
vi	Vietnamese	0.08%
uk	Ukrainian	0.07%
ko	Korean	0.06%
ca	Catalan	0.04%
sr	Serbian	0.04%
id	Indonesian	0.03%
cs	Czech	0.03%
fi	Finnish	0.03%

Table 7: Top 20 language distribution of the training data for Llama2, excluding code and unknown data. Adopted from Table 10 in Touvron et al. (2023).

Code	Language	Tokens (B)	Percentage
en	English	578.064	77.984%
de	German	25.954	3.501%
fr	French	24.094	3.250%
es	Spanish	15.654	2.112%
pl	Polish	10.764	1.452%
it	Italian	9.699	1.308%
nl	Dutch	7.690	1.037%
sv	Swedish	5.218	0.704%
tr	Turkish	4.855	0.655%
pt	Portuguese	4.701	0.634%
ru	Russian	3.932	0.530%
fi	Finnish	3.101	0.418%
cs	Czech	2.991	0.404%
zh	Chinese	2.977	0.402%
ja	Japanese	2.832	0.382%
no	Norwegian	2.695	0.364%
ko	Korean	1.444	0.195%
da	Danish	1.387	0.187%
id	Indonesian	1.175	0.159%
ar	Arabic	1.091	0.147%

Table 8: Top 20 language distribution of the training data for PaLM, excluding code and unknown data. Adopted from Table 28 in Chowdhery et al. (2023).

{
"da": "Vidal har, siden han flyttede til den catalanske hovedstad, spillet 49 kampe for klubben.",
"de": "Seit seinem Umzug in die katalanische Hauptstadt hatte Vidal für den Verein 49 Partien gespielt.",
"en": "Since moving to the Catalan-capital, Vidal had played 49 games for the club.",
"es": "Desde su mudanza a la capital catalana, Vidal jugó 49 partidos para el club.",
"fr": "Depuis son arrivée dans la capitale catalane, Vidal a joué 49 matchs pour le club.",
"id": "Sejak menetap di ibu kota Catalan, Vidal sudah bermain di 49 laga untuk klub ini.",
"it": "Dal suo arrivo nella capitale catalana, Vidal ha giocato per il club 49 partite.",
"ja": "カタルーニャの州都に移って以来、ビダルはクラブで49試合に出場しました。",
"ko": "바르셀로나로 이적한 후 비달은 클럽을 위해 49경기를 뛰었습니다.",
"nl": "Sinds hij verhuisde naar de Catalaanse hoofdstad heeft hij 49 wedstrijden gespeeld voor de club.",
"ru": "После переезда в столицу Каталонии Видаль провел за клуб 49 матчей.",
"tr": "Katalan başkentine taşındığından beri Vidal kulüp adına 49 maça çıktı.",
"zh": "自从转会到加泰罗尼亚的首府球队，维达尔已经为俱乐部踢了 49场比赛。",
},

Figure 9: A datapoint example from FLORES-101 of semantic-equivalent context-irrelevant sentences in all high resource languages we study in this work.

dataset), including the following 24 languages:

$$\mathcal{L}_H = \{\text{ar, ca, cs, da, de, en, es, fi, fr, id, it, ja, ko, nl, no, pl, pt, ru, sr, sv, tr, uk, vi, zh}\}. \quad (3)$$

The high overlap between the top languages of the two LLMs further supports the rationale for applying this list to other LLMs.

A.3.2 Languages We Evaluate

Tab. 9 presents the union of languages supported by the three datasets we evaluated (§ 3, datasets). Based on whether a language appears in the high-resource language list, we categorized the 24 languages into HRL and LRL groups, with 13 classified as HRL and 11 as LRL. Among them, only English and Chinese are present in all three datasets.

It is worth highlighting that the 11 LRLs span 7 distinct writing systems and 6 language families. This diversity suggests that when tokenizing inputs in these LRLs, they are unlikely to share common tokens with HRLs (9 out of 13 use the Latin script). Consequently, this limits the MLLMs' ability to leverage shared subwords or similar syntax structures for cross-lingual transfer across LRLs.

Code	Name in English	HRL/LRL	In Which Dataset(s)	Writing System	Family
bg	Bulgarian	Low	XL-WiC	Cyrillic	Indo-European
bn	Bengali	Low	MGSM	Bengali–Assamese	Indo-European
da	Danish	High	XL-WiC	Latin	Indo-European
de	German	High	MGSM, XL-WiC	Latin	Indo-European
en	English	High	MGSM, XL-WiC, XCOPA	Latin	Indo-European
es	Spanish	High	MGSM	Latin	Indo-European
et	Estonian	Low	XCOPA	Latin	Indo-European
fa	Persian	Low	XL-WiC	Arabic	Indo-European
fr	French	High	MGSM, XL-WiC	Latin	Indo-European
hr	Croatian	Low	XL-WiC	Latin	Indo-European
ht	Haitian	Low	XCOPA	Latin	French Creole
id	Indonesian	High	XCOPA	Latin	Austronesian
it	Italian	High	XL-WiC, XCOPA	Latin	Indo-European
ja	Japanese	High	MGSM, XL-WiC	Kana & Chinese Characters	Japonic
ko	Korean	High	XL-WiC	Hangul	Koreanic
nl	Dutch	High	XL-WiC	Latin	Indo-European
qu	Quechua	Low	XCOPA	Latin	Quechumaran
ru	Russian	High	MGSM	Cyrillic	Indo-European
sw	Swahili	Low	MGSM	Latin	Niger–Congo
ta	Tamil	Low	XCOPA	Tamil	Dravidian
te	Telegu	Low	MGSM	Telegu	Dravidian
th	Thai	Low	MGSM, XCOPA	Thai	Kra–Dai
tr	Turkish	High	XCOPA	Latin	Turkic
vi	Vietnamese	Low	XCOPA	Latin	Austroasiatic
zh	Chinese	High	MGSM, XL-WiC, XCOPA	Chinese Characters	Sino-Tibetan

Table 9: List of 25 languages we study and their properties, in ascending order of ISO 639-1 codes (for Standardization, 2023).

B Experiment Raw Results

B.1 ICL Modes Evaluation

The raw data for vanilla evaluation is recorded in Tabs. 11 to 13. McNemar's test results for ICL modes are in Tabs. 14 to 16. Significance (sig.) levels – *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$.

B.2 Context-Irrelevant Sentence

The raw data for CIS is recorded in Tabs. 17 to 19. McNemar's test results for CIS modes are in Tabs. 20 to 22.

C ICL Behavioral Analysis

C.1 Specilized Neuron

Inspired by the universal concept space (Wendler et al., 2024; Zhao et al., 2024; Wu et al., 2024), we hypothesize that MLLMs could activate more cross-lingual capabilities by aligning different linguistic representations. To validate the above hypothesis, we seek to find patterns in neuron behavior between ICL modes. Following Tan et al. (2024); Tang et al. (2024); Kojima et al. (2024); Mu et al. (2024); Zhao et al. (2024); Xu et al. (2024), we look at the activations of neurons in the multilayer perceptron (MLP, or *Feedforward Network, FFN*) modules of the MLLMs.

C.1.1 Identifying Top-Activated Neurons

Each neuron in every MLP layer of the model is assigned a dedicated counter, initialized to 0. During vanilla evaluation, we monitor the activation of every neuron in the forward pass. Since LLMs typically employ ReLU-like (Agarap, 2018) activation functions (e.g., SwiGLU (Shazeer, 2020) for Llama series), a positive activation value can be interpreted as the neuron being "activated". If a neuron is "activated", we increment the corresponding counter by 1, otherwise no action. To ensure balanced input across our three datasets, we curated a COMBINED dataset, see App. A.2 for details. After processing the inputs of a single ICL mode, each neuron accumulates an "activated" count. The neurons with the highest counts are identified as specialized neurons attributed to this ICL mode.

We employ two methods for selecting the most activated neurons. Top-k selects neurons in the top k percentile (Tang et al., 2024), while top-p selects neurons progressively until their cumulative activation counts reach p (%) of the sum of all activation values (Tan et al., 2024).

C.2 `Multilingual`-specific Neurons Overlap Most with `Native`-specific Neurons

We examined the overlaps among the most-activated neurons (*specialized neurons*) across different ICL modes by calculating the Intersection

IoU (%)	All Langs	LRL	HRL
English– Multilingual– Native			
Llama3.1-8B-Instruct			
Native- English	61.82	56.81	68.50
Native- Multilingual	78.84	66.19	85.10
English- Multilingual	65.84	66.89	64.60
Qwen2-7B-Instruct			
Native- English	70.61	66.05	81.22
Native- Multilingual	85.13	77.40	91.31
English- Multilingual	78.24	79.83	77.46
English– Chinese– Native			
Llama3.1-8B-Instruct			
Native- English	61.82	56.81	68.50
Native- Chinese	60.58	55.35	65.73
English- Chinese	56.52	57.94	55.72
Qwen2-7B-Instruct			
Native- English	70.61	66.05	81.22
Native- Chinese	73.41	69.39	82.18
English- Chinese	77.07	78.34	76.51

Table 10: The IoU score of most-activated neurons between every pair of ICL modes in triplets English– Multilingual– Native and English– Chinese– Native. Neurons were selected by first filtering out neurons outside the first 8 and last 8 MLP layers, and applying top-k method with $k = 0.7$.

over Union (IoU) scores. For ICL modes M_1 and M_2, with specialized neurons denoted as sets S_1 and S_2, their overlap is quantified by Eq. (4):

$$\text{IoU}\,(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}. \tag{4}$$

Prior research (Tang et al., 2024; Zhao et al., 2024) has discovered that *language-specific neurons* are located primarily in the models' top and bottom layers. Because we want to explain the multilingual reasoning capabilities of a model, we only consider neurons that belong to a certain prefix or suffix of the models' layers in an effort to restrict our selected neuron sets to be mainly language-specific neurons.

The similarity in performance between Multilingual and Native can be explained by the high overlap in the sets of most-activated neurons. On the other hand, the poorer performance of English can be explained by the low overlap between English most-activated neurons and other ICL modes .

The same experiment was also performed but with Multilingual replaced by HRL Chinese. In this case, the patterns were less obvious and model-specific. This result aligns with our findings in vanilla evaluation that English $\leq$ Non-English HRL Monolingual $\leq$ Multilingual (§4.2).

We further split this neuron experiment to either use only LRL or HRL ICL modes when recording neuron activations. We observed that HRL tends to activate similar neurons between Native and Multilingual, whereas LRL tends to activate similar neurons between English and Multilingual.

MGSM	bn	de	en	es	fr	ja	ru	sw	te	th	zh	LRL Avg	HRL Avg	ALL Avg
Llama3-8B-Instruct														
English	66.40	76.40	86.40	78.80	77.60	66.40	77.20	59.20	60.00	71.20	75.60	64.20	76.91	72.29
French	67.60	77.60	86.00	77.60	75.20	70.00	79.60	56.40	59.60	68.00	70.40	62.90$_{1.30\downarrow}$	76.63$_{0.28\downarrow}$	71.64$_{0.65\downarrow}$
Chinese	66.80	77.20	82.80	79.60	74.80	68.00	76.40	55.60	59.20	70.40	72.80	63.00$_{1.20\downarrow}$	75.94$_{0.97\downarrow}$	71.24$_{1.05\downarrow}$
Japanese	66.80	78.80	83.20	76.00	74.80	70.80	76.40	56.40	56.80	68.80	68.00	62.20$_{2.00\downarrow}$	75.43$_{1.48\downarrow}$	70.62$_{1.67\downarrow}$
Multilingual	65.20	79.60	84.40	77.60	74.00	69.60	76.80	52.40	53.60	69.60	70.00	60.20$_{4.00\downarrow}$	76.00$_{0.91\downarrow}$	70.25$_{2.04\downarrow}$
Native	64.80	76.80	86.40	80.00	75.20	70.80	76.80	58.40	54.80	70.40	72.80	62.10$_{2.10\downarrow}$	76.97$_{0.06\uparrow}$	71.56$_{0.73\downarrow}$
Transl-Lang→En	63.60	73.20	86.40	78.00	74.00	60.40	77.60	69.60	60.00	46.40	58.80	59.90$_{4.30\downarrow}$	72.63$_{4.28\downarrow}$	68.00$_{4.29\downarrow}$
Transl-En→Lang	65.20	78.80	86.40	79.60	76.00	68.40	76.40	58.80	52.80	69.20	73.60	61.50$_{2.70\downarrow}$	77.03$_{0.12\uparrow}$	71.38$_{0.91\downarrow}$
Llama3.1-8B-Instruct														
English	52.40	69.20	87.20	63.60	76.80	68.00	78.80	67.20	39.60	69.20	75.20	57.10	74.11	67.93
French	62.80	74.40	89.20	82.40	82.40	69.60	79.20	69.60	45.20	70.00	76.80	61.90$_{4.80\uparrow}$	79.14$_{5.03\uparrow}$	72.87$_{4.94\uparrow}$
Chinese	66.00	76.80	87.20	83.20	78.00	67.60	79.60	70.00	48.40	69.20	77.60	63.40$_{6.30\uparrow}$	78.57$_{4.46\uparrow}$	73.05$_{5.12\uparrow}$
Japanese	66.40	76.80	86.00	80.80	78.00	67.20	79.60	72.80	58.00	75.20	77.60	68.10$_{11.00\uparrow}$	78.00$_{3.89\uparrow}$	74.40$_{6.47\uparrow}$
Multilingual	68.00	76.40	88.00	84.80	80.40	69.20	80.40	68.80	55.60	71.60	75.20	66.00$_{8.90\uparrow}$	79.20$_{5.09\uparrow}$	74.40$_{6.47\uparrow}$
Native	67.20	80.40	87.20	81.20	82.40	67.20	80.00	72.40	58.00	76.40	77.60	68.50$_{11.40\uparrow}$	79.43$_{5.32\uparrow}$	75.45$_{7.52\uparrow}$
Transl-Lang→En	62.80	74.80	87.20	82.00	77.60	62.80	81.60	68.00	62.00	47.20	57.60	60.00$_{2.90\uparrow}$	74.80$_{0.69\uparrow}$	69.42$_{1.49\uparrow}$
Transl-En→Lang	67.60	80.00	87.20	82.80	83.60	70.80	80.80	70.80	59.60	76.40	79.20	68.60$_{11.50\uparrow}$	80.63$_{6.52\uparrow}$	76.25$_{8.32\uparrow}$
Qwen2-7B-Instruct														
English	57.20	74.00	90.40	82.00	80.00	67.60	80.40	20.80	23.20	73.60	79.20	43.70	79.09	66.22
French	54.80	74.00	92.00	82.00	79.60	66.80	79.20	22.40	20.80	73.60	80.40	42.90$_{0.80\downarrow}$	79.14$_{0.05\uparrow}$	65.96$_{0.26\downarrow}$
Chinese	56.00	76.40	92.00	81.20	77.60	71.20	79.60	28.80	20.40	73.60	85.20	44.70$_{1.00\uparrow}$	80.46$_{1.37\uparrow}$	67.45$_{1.23\uparrow}$
Japanese	51.20	72.80	88.80	78.80	76.00	75.20	79.20	27.20	20.80	72.40	80.80	42.90$_{0.80\downarrow}$	78.80$_{0.29\downarrow}$	65.75$_{0.47\downarrow}$
Multilingual	64.80	77.20	89.20	82.80	81.60	70.40	82.00	28.40	23.60	73.20	79.60	47.50$_{3.80\uparrow}$	80.40$_{1.31\uparrow}$	68.44$_{2.22\uparrow}$
Native	72.00	83.60	90.40	82.80	79.60	75.20	83.20	32.40	40.40	76.80	85.20	55.40$_{11.70\uparrow}$	82.86$_{3.77\uparrow}$	72.87$_{6.65\uparrow}$
Transl-Lang→En	66.00	76.00	90.40	79.60	79.20	64.00	77.60	72.40	61.20	47.60	58.40	61.80$_{18.10\uparrow}$	75.03$_{4.06\downarrow}$	70.22$_{4.00\uparrow}$
Transl-En→Lang	72.40	81.20	90.40	82.40	80.00	69.20	81.20	32.80	43.20	74.80	80.80	55.80$_{12.10\uparrow}$	80.74$_{1.65\uparrow}$	71.67$_{5.45\uparrow}$
Qwen2.5-7B-Instruct														
English	75.20	82.40	94.40	88.80	87.60	76.80	88.00	30.80	48.80	82.80	86.80	59.40	86.40	76.58
French	74.00	85.20	92.40	90.00	85.60	78.80	86.80	33.60	51.20	82.40	84.00	60.30$_{0.90\uparrow}$	86.11$_{0.29\downarrow}$	76.73$_{0.15\uparrow}$
Chinese	77.20	85.20	94.00	88.80	86.00	81.60	88.00	31.20	50.40	81.20	86.40	60.00$_{0.60\uparrow}$	87.14$_{0.74\uparrow}$	77.27$_{0.69\uparrow}$
Japanese	74.80	84.80	94.80	90.80	88.00	81.20	88.40	32.80	50.80	83.20	85.60	60.40$_{1.00\uparrow}$	87.66$_{1.26\uparrow}$	77.75$_{1.17\uparrow}$
Multilingual	76.40	86.80	92.80	89.60	88.00	78.40	87.20	30.40	50.00	81.20	86.00	59.50$_{0.10\uparrow}$	86.97$_{0.57\uparrow}$	76.98$_{0.40\uparrow}$
Native	75.20	86.80	94.40	89.20	85.60	81.20	87.60	35.60	46.00	84.40	86.40	60.30$_{0.90\uparrow}$	87.31$_{0.91\uparrow}$	77.49$_{0.91\uparrow}$
Transl-Lang→En	70.40	79.60	94.40	83.60	82.40	64.00	81.60	72.80	62.40	48.00	64.80	63.40$_{4.60\uparrow}$	78.63$_{7.77\downarrow}$	73.09$_{3.49\downarrow}$
Transl-En→Lang	74.80	85.60	94.40	88.80	84.40	80.40	87.20	35.20	46.80	82.80	88.00	59.90$_{0.50\uparrow}$	86.97$_{0.57\uparrow}$	77.13$_{0.55\uparrow}$
NeMo-12B-Instruct														
English	66.80	75.60	90.80	81.20	80.00	64.40	83.60	42.00	54.00	65.20	76.80	57.00	78.91	70.95
French	66.00	81.20	92.40	82.00	81.60	74.80	83.20	46.40	70.40	74.40	76.40	64.30$_{7.30\uparrow}$	81.66$_{2.75\uparrow}$	75.35$_{4.40\uparrow}$
Chinese	70.40	81.60	91.60	81.60	82.00	73.20	84.80	49.20	69.60	69.20	77.20	64.60$_{7.60\uparrow}$	81.71$_{2.80\uparrow}$	75.49$_{4.54\uparrow}$
Japanese	67.20	84.40	90.00	85.60	83.20	74.40	84.80	45.60	69.60	72.00	76.00	63.60$_{6.60\uparrow}$	82.63$_{3.72\uparrow}$	75.71$_{4.76\uparrow}$
Multilingual	67.20	82.00	90.40	82.80	77.60	71.60	83.20	50.80	66.40	68.80	80.00	63.30$_{6.30\uparrow}$	81.09$_{2.18\uparrow}$	74.62$_{3.67\uparrow}$
Native	66.40	81.20	90.80	82.00	81.60	74.40	81.60	58.00	67.60	71.20	77.20	65.80$_{8.80\uparrow}$	81.26$_{2.35\uparrow}$	75.64$_{4.69\uparrow}$
Transl-Lang→En	65.20	76.80	90.80	82.00	78.80	62.00	80.00	71.60	62.40	47.20	61.60	61.60$_{4.60\uparrow}$	76.00$_{2.91\downarrow}$	70.76$_{0.19\downarrow}$
Transl-En→Lang	68.80	83.60	90.80	80.40	82.00	74.00	85.60	57.60	66.80	73.20	77.60	66.60$_{9.60\uparrow}$	82.00$_{3.09\uparrow}$	76.40$_{5.45\uparrow}$
Aya-Expanse-8B														
English	39.60	75.60	82.40	81.60	72.40	67.20	77.20	20.00	17.20	40.80	71.20	29.40	75.37	58.65
French	43.60	74.40	81.60	80.00	75.20	67.60	77.60	19.60	23.20	36.40	74.00	30.70$_{1.30\uparrow}$	75.77$_{0.40\uparrow}$	59.38$_{0.73\uparrow}$
Chinese	44.00	74.40	80.40	77.60	73.20	66.00	77.20	20.00	22.40	40.40	76.40	31.70$_{2.30\uparrow}$	75.03$_{0.34\downarrow}$	59.27$_{0.62\uparrow}$
Japanese	42.80	72.40	83.20	79.20	72.80	66.80	77.20	20.40	20.00	38.40	72.00	30.40$_{1.00\uparrow}$	74.80$_{0.57\downarrow}$	58.65$_{0.00-}$
Multilingual	46.80	74.00	83.60	78.00	72.80	67.60	79.60	19.20	17.60	36.80	72.00	30.10$_{0.70\uparrow}$	75.37$_{0.00-}$	58.91$_{0.26\uparrow}$
Native	44.80	77.60	82.40	79.60	75.20	66.80	79.20	19.60	22.00	44.00	76.40	32.60$_{3.20\uparrow}$	76.74$_{1.37\uparrow}$	60.69$_{2.04\uparrow}$
Transl-Lang→En	64.40	71.20	82.40	76.40	74.40	57.60	69.20	65.20	62.80	48.00	59.60	60.10$_{30.70\uparrow}$	70.11$_{5.26\downarrow}$	66.47$_{7.82\uparrow}$
Transl-En→Lang	46.40	74.80	82.40	80.00	74.80	66.00	78.80	19.20	20.80	42.40	76.00	32.20$_{2.80\uparrow}$	76.11$_{0.74\uparrow}$	60.15$_{1.50\uparrow}$
GPT3.5-turbo														
English	39.60	75.20	86.00	76.80	62.80	59.20	66.40	63.60	12.80	60.80	67.20	44.20	70.51	60.95
French	34.00	74.80	86.00	84.80	79.20	66.00	67.60	63.20	15.20	55.60	74.40	42.00$_{2.20\downarrow}$	76.11$_{5.60\uparrow}$	63.71$_{2.76\uparrow}$
Chinese	30.40	78.80	83.20	78.40	77.20	69.20	77.60	67.20	15.60	62.40	73.20	43.90$_{0.30\downarrow}$	76.80$_{6.29\uparrow}$	64.84$_{3.89\uparrow}$
Japanese	27.60	78.80	85.20	82.00	72.40	73.20	74.40	69.60	14.00	61.20	76.00	43.10$_{1.10\downarrow}$	77.43$_{6.92\uparrow}$	64.95$_{4.00\uparrow}$
Multilingual	54.40	79.60	83.60	79.20	73.60	68.00	75.20	68.00	24.40	57.20	74.40	51.00$_{6.80\uparrow}$	76.23$_{5.72\uparrow}$	67.05$_{6.10\uparrow}$
Native	57.20	79.60	86.00	80.40	81.60	75.20	77.60	73.60	30.00	58.80	74.00	54.90$_{10.70\uparrow}$	79.26$_{8.75\uparrow}$	70.40$_{9.45\uparrow}$
GPT4o-mini														
English	87.20	90.80	94.80	92.00	87.20	84.80	92.00	83.20	84.00	88.80	90.00	85.80	90.23	88.62
French	87.20	90.80	94.40	92.80	89.20	82.40	90.80	85.20	84.00	88.80	87.60	86.30$_{0.50\uparrow}$	89.71$_{0.52\downarrow}$	88.47$_{0.15\downarrow}$
Chinese	86.80	90.80	93.60	93.20	90.00	83.20	91.20	85.20	84.40	90.00	90.80	86.60$_{0.80\uparrow}$	90.40$_{0.17\uparrow}$	89.02$_{0.40\uparrow}$
Japanese	85.20	89.60	94.80	92.80	86.80	86.00	92.00	82.80	81.60	88.40	87.60	84.50$_{1.30\downarrow}$	89.94$_{0.29\downarrow}$	87.96$_{0.66\downarrow}$
Multilingual	86.40	90.00	92.80	94.00	89.20	84.00	92.40	84.00	80.40	88.00	89.20	84.70$_{1.10\downarrow}$	90.23$_{0.00-}$	88.22$_{0.40\downarrow}$
Native	85.20	88.00	94.80	91.20	89.20	85.20	90.40	85.60	81.60	88.40	90.00	85.20$_{0.60\downarrow}$	89.66$_{0.57\downarrow}$	88.04$_{0.58\downarrow}$

Table 11: Accuracies (%) of English, Multilingual, Native, all Monolingual ICL modes (French, Chinese and Japanese) and two translation strategies (Transl-Lang→En, Transl-En→Lang) across 11 languages of the MGSM dataset. AVG represents the average accuracy of the language set (LRLs, HRLs or All languages). The underlined languages in the table header are LRLs, otherwise HRLs. The subscript indicates the performance increase↑ (or decrease↓) of all other modes compared to the English ICL mode.

XCOPA	en	et	ht	id	it	qu	sw	ta	th	tr	vi	zh	LRL AVG	HRL AVG	ALL AVG
Llama3-8B-Instruct															
English	95.20	55.80	10.20	79.60	86.60	7.60	40.00	59.40	69.60	72.00	81.00	87.00	46.23	84.08	62.00
Italian	93.80	59.80	46.80	81.00	89.60	41.20	57.40	58.80	73.40	76.00	80.20	88.20	59.66$_{13.43\uparrow}$	85.72$_{1.64\uparrow}$	70.52$_{8.52\uparrow}$
Chinese	93.80	59.80	52.80	82.40	85.60	47.60	55.40	59.00	79.00	74.60	79.60	90.80	61.89$_{15.66\uparrow}$	85.44$_{1.36\uparrow}$	71.70$_{9.70\uparrow}$
Multilingual	94.60	57.80	51.80	81.60	87.80	46.40	60.40	60.80	79.20	78.80	80.40	88.80	62.40$_{16.17\uparrow}$	86.32$_{2.24\uparrow}$	72.37$_{10.37\uparrow}$
Native	95.20	68.60	61.60	85.00	89.60	50.40	62.00	65.80	77.80	79.80	84.80	90.80	67.29$_{21.06\uparrow}$	88.08$_{4.00\uparrow}$	75.95$_{13.95\uparrow}$
Transl-Lang→En	95.20	84.00	69.80	83.00	88.40	61.00	69.00	70.40	66.00	86.20	85.20	85.20	72.20$_{25.97\uparrow}$	87.60$_{3.52\uparrow}$	78.62$_{16.62\uparrow}$
Transl-En→Lang	95.20	69.60	62.00	87.40	89.20	52.00	62.00	63.80	78.60	79.80	84.00	89.20	67.43$_{21.20\uparrow}$	88.16$_{4.08\uparrow}$	76.07$_{14.07\uparrow}$
Llama3.1-8B-Instruct															
English	95.60	65.20	27.00	84.20	88.40	26.00	52.60	62.40	73.80	76.80	84.40	89.80	55.91	86.96	68.85
Italian	95.00	62.20	28.40	86.00	92.80	32.60	61.60	70.20	76.60	78.20	85.00	90.80	59.51$_{3.60\uparrow}$	88.56$_{1.60\uparrow}$	71.62$_{2.77\uparrow}$
Chinese	95.00	65.20	48.40	83.80	88.20	32.20	58.80	68.80	76.40	78.60	86.00	91.40	62.26$_{6.35\uparrow}$	87.40$_{0.44\uparrow}$	72.73$_{3.88\uparrow}$
Multilingual	96.00	60.40	57.20	87.60	90.80	46.80	61.60	70.80	78.60	83.00	87.40	90.80	66.11$_{10.20\uparrow}$	89.64$_{2.68\uparrow}$	75.92$_{7.07\uparrow}$
Native	95.60	72.40	66.20	89.80	92.80	52.60	66.60	75.20	80.80	84.40	87.60	91.40	71.63$_{15.72\uparrow}$	90.80$_{3.84\uparrow}$	79.62$_{10.77\uparrow}$
Transl-Lang→En	95.60	87.60	74.60	88.20	89.60	68.20	73.20	74.20	72.60	88.00	86.80	87.00	76.74$_{20.83\uparrow}$	89.68$_{2.72\uparrow}$	82.13$_{13.28\uparrow}$
Transl-En→Lang	95.60	74.40	63.40	89.00	90.00	52.20	65.20	74.00	78.40	83.60	85.80	92.00	70.49$_{14.58\uparrow}$	90.04$_{3.08\uparrow}$	78.63$_{9.78\uparrow}$
Qwen2-7B-Instruct															
English	97.00	61.80	50.60	88.00	90.20	49.80	53.20	58.40	77.80	75.40	84.40	91.00	62.29	88.32	73.13
Italian	92.20	66.40	51.60	88.40	95.40	52.20	54.40	59.80	79.80	78.20	83.80	87.20	64.00$_{1.71\uparrow}$	88.28$_{0.04\downarrow}$	74.12$_{0.99\uparrow}$
Chinese	88.60	65.00	51.80	81.20	86.00	50.20	53.00	60.00	79.00	77.60	83.60	93.60	63.23$_{0.94\uparrow}$	85.40$_{2.92\downarrow}$	72.47$_{0.66\downarrow}$
Multilingual	96.00	63.20	53.80	90.60	94.00	53.00	53.40	59.60	80.40	77.60	83.40	93.00	63.83$_{1.54\uparrow}$	90.24$_{1.92\uparrow}$	74.83$_{1.70\uparrow}$
Native	97.00	71.20	54.80	93.00	95.40	51.40	60.20	63.20	83.60	81.20	89.00	93.60	67.63$_{5.34\uparrow}$	92.04$_{3.72\uparrow}$	77.80$_{4.67\uparrow}$
Transl-Lang→En	97.00	88.40	80.00	91.00	92.00	75.60	79.80	82.80	76.20	90.20	88.40	89.40	81.60$_{19.31\uparrow}$	91.92$_{3.60\uparrow}$	85.90$_{12.77\uparrow}$
Transl-En→Lang	97.00	67.20	54.60	91.20	94.80	51.00	56.80	61.60	83.00	80.20	86.40	91.80	65.80$_{3.51\uparrow}$	91.00$_{2.68\uparrow}$	76.30$_{3.17\uparrow}$
Qwen2.5-7B-Instruct															
English	97.40	62.20	56.40	89.40	93.20	50.80	53.40	58.20	83.40	80.20	88.40	93.60	64.69	90.76	75.55
Italian	96.40	65.20	57.80	89.00	95.40	49.00	52.20	58.40	82.00	83.60	87.20	92.80	64.54$_{0.15\downarrow}$	91.44$_{0.68\uparrow}$	75.75$_{0.20\uparrow}$
Chinese	95.80	65.00	58.40	89.00	92.40	50.80	51.40	58.60	83.40	82.00	89.80	94.60	65.34$_{0.65\uparrow}$	90.76$_{0.00-}$	75.93$_{0.38\uparrow}$
Multilingual	97.00	65.40	56.80	91.80	94.00	49.20	49.60	59.20	83.60	84.00	88.60	92.40	64.63$_{0.06\downarrow}$	91.84$_{1.08\uparrow}$	75.97$_{0.42\uparrow}$
Native	97.40	69.60	62.80	91.40	95.40	50.60	54.00	61.40	85.40	84.40	90.00	94.60	67.69$_{3.00\uparrow}$	92.64$_{1.88\uparrow}$	78.08$_{2.53\uparrow}$
Transl-Lang→En	97.40	87.80	80.60	91.20	91.20	75.00	77.40	80.60	74.20	89.80	87.80	88.00	80.49$_{15.80\uparrow}$	91.52$_{0.76\uparrow}$	85.08$_{9.53\uparrow}$
Transl-En→Lang	97.40	67.40	61.20	91.00	96.00	46.80	53.60	60.40	85.40	82.80	88.80	95.20	66.23$_{1.54\uparrow}$	92.48$_{1.72\uparrow}$	77.17$_{1.62\uparrow}$
NeMo-12B-Instruct															
English	96.60	57.60	58.00	83.00	93.20	50.60	51.60	73.40	64.60	73.60	80.00	91.20	62.26	87.52	72.78
Italian	96.00	57.40	55.40	82.00	95.80	48.60	53.80	73.00	64.80	73.00	81.60	90.00	62.09$_{0.17\downarrow}$	87.36$_{0.16\downarrow}$	72.62$_{0.16\downarrow}$
Chinese	96.40	58.20	52.00	83.00	92.60	49.00	53.80	70.20	66.80	71.00	81.00	91.60	61.57$_{0.69\downarrow}$	86.92$_{0.60\downarrow}$	72.13$_{0.65\downarrow}$
Multilingual	95.80	60.20	54.00	85.80	94.40	48.80	56.00	76.20	62.80	72.60	82.60	92.20	62.94$_{0.68\uparrow}$	88.16$_{0.64\uparrow}$	73.45$_{0.67\uparrow}$
Native	96.60	74.00	64.00	87.40	95.80	48.80	62.20	82.20	79.00	80.00	86.20	91.60	70.91$_{8.65\uparrow}$	90.28$_{2.76\uparrow}$	78.98$_{6.20\uparrow}$
Transl-Lang→En	96.60	88.00	75.40	87.60	89.40	70.00	74.20	77.40	74.00	88.20	85.80	84.80	77.83$_{15.57\uparrow}$	89.32$_{1.80\uparrow}$	82.62$_{9.84\uparrow}$
Transl-En→Lang	96.60	71.40	63.00	88.00	94.40	49.20	60.60	76.40	73.20	80.60	85.40	93.00	68.46$_{6.20\uparrow}$	90.52$_{3.00\uparrow}$	77.65$_{4.87\uparrow}$
Aya-Expanse-8B															
English	95.40	28.20	17.60	83.80	84.20	0.00	11.20	45.20	10.00	80.40	73.60	77.60	26.54	84.28	50.60
Italian	92.00	15.40	18.40	86.40	91.40	0.20	11.20	45.80	34.60	82.20	79.60	85.60	29.31$_{2.77\uparrow}$	87.52$_{3.24\uparrow}$	53.57$_{2.97\uparrow}$
Chinese	90.60	39.40	34.80	81.00	82.80	0.00	17.60	38.60	23.00	79.00	78.40	92.20	33.11$_{6.57\uparrow}$	85.12$_{0.84\uparrow}$	54.78$_{4.18\uparrow}$
Multilingual	93.40	52.20	52.00	88.00	90.00	5.60	46.00	58.20	43.60	84.00	83.20	90.20	48.69$_{22.15\uparrow}$	89.12$_{4.84\uparrow}$	65.53$_{14.93\uparrow}$
Native	95.40	54.00	56.20	88.80	91.40	53.40	53.40	69.40	62.40	85.60	86.20	92.20	62.14$_{35.60\uparrow}$	90.68$_{6.40\uparrow}$	74.03$_{23.43\uparrow}$
Transl-Lang→En	95.40	84.40	75.20	86.60	86.80	67.40	74.40	74.60	67.80	86.40	84.20	85.60	75.43$_{48.89\uparrow}$	88.16$_{3.88\uparrow}$	80.73$_{30.13\uparrow}$
Transl-En→Lang	95.40	54.20	54.40	89.40	90.80	45.80	51.00	65.80	60.00	83.80	86.00	90.60	59.60$_{33.06\uparrow}$	90.00$_{5.72\uparrow}$	72.27$_{21.67\uparrow}$
GPT3.5-turbo															
English	96.00	77.20	56.80	83.00	88.80	48.40	70.80	52.00	64.80	76.20	74.00	83.80	63.43	85.56	72.65
Italian	95.00	78.60	57.20	83.20	91.20	49.20	71.60	49.40	60.40	79.40	77.40	85.60	63.40$_{0.03\downarrow}$	86.88$_{1.32\uparrow}$	73.18$_{0.53\uparrow}$
Chinese	94.40	77.20	58.60	84.40	86.80	48.80	69.80	50.00	62.00	76.80	75.20	86.80	63.09$_{0.34\downarrow}$	85.84$_{0.28\uparrow}$	72.57$_{0.08\downarrow}$
Multilingual	93.80	75.00	56.80	87.40	89.60	49.20	71.40	48.00	62.80	85.80	75.80	86.80	62.71$_{0.72\downarrow}$	88.68$_{3.12\uparrow}$	73.53$_{0.88\uparrow}$
Native	96.00	85.20	67.60	87.20	90.80	48.00	77.20	53.20	61.40	87.60	77.60	87.60	67.17$_{3.74\uparrow}$	89.80$_{4.24\uparrow}$	76.60$_{3.95\uparrow}$
GPT4o-mini															
English	98.60	93.20	80.00	94.20	97.60	49.80	84.20	83.40	88.20	95.20	92.80	95.60	81.66	96.24	87.73
Italian	98.80	91.60	74.40	95.00	98.20	49.20	82.60	84.40	89.00	95.60	92.80	96.40	80.57$_{1.09\downarrow}$	96.80$_{0.56\uparrow}$	87.33$_{0.40\downarrow}$
Chinese	98.00	93.40	81.00	94.20	97.80	49.80	84.00	84.40	88.80	94.80	93.40	95.00	82.11$_{0.45\uparrow}$	95.96$_{0.28\downarrow}$	87.88$_{0.15\uparrow}$
Multilingual	98.60	93.80	80.00	96.00	98.20	50.20	85.00	86.20	92.40	96.20	94.40	95.20	83.14$_{1.48\uparrow}$	96.84$_{0.60\uparrow}$	88.85$_{1.12\uparrow}$
Native	98.60	94.80	89.60	95.20	98.20	52.20	87.60	88.80	93.80	95.20	95.00	95.20	85.97$_{4.31\uparrow}$	96.48$_{0.24\uparrow}$	90.35$_{2.62\uparrow}$

Table 12: Accuracies (%) of English, Multilingual, Native, both Monolingual ICL modes (Italian and Chinese) and two translation strategies (Transl-Lang→En, Transl-En→Lang) across 12 languages of the XCOPA dataset. AVG represents the average accuracy of the language set (LRLs, HRLs or All languages). The underlined languages in the table header are LRLs, otherwise HRLs. The subscript indicates the performance increase↑ (or decrease↓) of all other modes compared to the English ICL mode.

XL-WiC	bg	da	de	en	et	fa	fr	hr	it	ja	ko	nl	zh	LRL AVG	HRL AVG	ALL AVG
Llama3-8B-Instruct																
English	55.13	66.15	59.49	67.44	55.38	63.33	59.49	55.64	53.85	54.62	56.67	55.90	64.10	57.37	59.74	59.01
French	57.95	63.08	66.67	64.62	52.82	68.21	66.15	57.18	56.15	55.13	51.79	62.82	65.38	59.04$_{1.67\uparrow}$	61.31$_{1.57\uparrow}$	60.61$_{1.60\uparrow}$
Chinese	56.67	64.10	64.87	63.59	55.38	63.08	58.97	54.87	62.31	57.18	48.21	63.85	63.33	57.50$_{0.13\uparrow}$	60.71$_{0.97\uparrow}$	59.72$_{0.71\uparrow}$
Japanese	59.74	61.79	66.15	65.38	52.56	70.77	60.00	56.67	59.23	58.97	55.13	64.87	63.33	59.94$_{2.57\uparrow}$	61.65$_{1.91\uparrow}$	61.12$_{2.11\uparrow}$
Multilingual	57.18	60.00	62.82	64.10	53.85	69.23	60.00	56.92	58.97	58.46	57.44	62.82	58.72	59.29$_{1.92\uparrow}$	60.37$_{0.63\uparrow}$	60.04$_{1.03\uparrow}$
Native	63.59	55.90	69.23	67.44	62.05	68.72	66.15	58.21	59.49	58.97	66.67	66.41	63.33	63.14$_{5.77\uparrow}$	63.73$_{3.99\uparrow}$	63.55$_{4.54\uparrow}$
Llama3.1-8B-Instruct																
English	51.54	50.77	61.28	66.92	44.62	29.74	56.67	51.79	15.90	48.46	33.85	51.28	57.44	44.42	49.17	47.71
French	54.62	60.00	66.41	64.62	49.74	22.56	62.31	57.44	52.56	49.49	53.33	65.13	54.10	46.09$_{1.67\uparrow}$	58.66$_{9.49\uparrow}$	54.79$_{7.08\uparrow}$
Chinese	54.87	62.82	62.31	61.79	53.08	55.64	56.15	57.95	56.67	49.74	48.21	62.31	62.05	55.38$_{10.96\uparrow}$	58.01$_{8.84\uparrow}$	57.20$_{9.49\uparrow}$
Japanese	54.36	60.00	63.59	60.00	47.69	63.33	58.72	52.05	58.21	53.59	48.97	58.21	56.41	54.36$_{9.94\uparrow}$	57.52$_{8.35\uparrow}$	56.55$_{8.84\uparrow}$
Multilingual	57.69	60.00	65.38	62.56	55.13	58.46	57.95	56.92	55.38	54.36	52.31	64.62	58.46	57.05$_{12.63\uparrow}$	59.00$_{9.83\uparrow}$	58.40$_{10.69\uparrow}$
Native	61.79	64.10	68.46	66.92	62.05	70.51	62.31	57.18	56.15	53.59	63.08	69.49	62.05	62.88$_{18.46\uparrow}$	62.91$_{13.74\uparrow}$	62.90$_{15.19\uparrow}$
Qwen2-7B-Instruct																
English	28.21	38.46	66.67	68.46	56.92	53.85	63.33	54.87	39.23	1.28	15.90	64.36	0.77	48.46	39.83	42.49
French	53.59	51.54	64.87	66.92	53.85	58.21	63.08	56.41	49.74	25.90	33.08	62.82	14.10	55.51$_{7.05\uparrow}$	48.01$_{8.18\uparrow}$	50.32$_{7.83\uparrow}$
Chinese	47.18	27.44	68.46	67.44	57.44	58.97	61.79	55.13	40.51	56.41	37.69	60.00	68.72	54.68$_{6.22\uparrow}$	54.27$_{14.44\uparrow}$	54.40$_{11.91\uparrow}$
Japanese	56.15	30.26	66.41	66.92	56.15	60.26	61.79	56.67	47.95	60.77	59.49	66.41	40.26	57.31$_{8.85\uparrow}$	55.58$_{15.75\uparrow}$	56.11$_{13.62\uparrow}$
Multilingual	53.59	60.00	65.64	65.64	58.46	58.72	60.26	54.36	56.67	58.72	66.92	67.18	57.95	56.28$_{7.82\uparrow}$	62.11$_{22.28\uparrow}$	60.32$_{17.83\uparrow}$
Native	55.13	62.05	69.49	68.46	59.23	62.05	63.08	54.62	60.51	60.77	68.21	64.87	68.72	57.76$_{9.30\uparrow}$	65.13$_{25.30\uparrow}$	62.86$_{20.37\uparrow}$
Qwen2.5-7B-Instruct																
English	58.97	61.28	73.33	70.51	55.64	53.59	65.90	63.08	57.95	55.64	64.10	67.69	59.74	57.82	64.02	62.11
French	55.13	57.18	68.97	65.13	55.38	54.10	64.87	57.18	62.05	57.95	62.82	65.64	62.56	55.45$_{2.37\downarrow}$	63.02$_{1.00\downarrow}$	60.69$_{1.42\downarrow}$
Chinese	53.33	54.87	67.18	67.18	54.62	51.28	63.85	57.44	57.95	64.87	62.82	61.79	66.67	54.17$_{3.65\downarrow}$	63.02$_{1.00\downarrow}$	60.30$_{1.81\downarrow}$
Japanese	53.59	54.62	67.44	67.18	54.10	49.74	63.08	57.18	56.41	64.10	63.33	65.13	60.00	53.65$_{4.17\downarrow}$	62.36$_{1.66\downarrow}$	59.68$_{2.43\downarrow}$
Multilingual	57.44	60.51	69.23	68.21	54.62	55.38	61.28	56.41	57.18	64.36	66.67	67.69	64.62	55.96$_{1.86\downarrow}$	64.42$_{0.40\uparrow}$	61.81$_{0.30\downarrow}$
Native	60.00	63.33	72.56	70.51	55.90	63.33	64.87	55.64	62.31	64.10	70.77	72.82	66.67	58.72$_{0.90\uparrow}$	67.55$_{3.53\uparrow}$	64.83$_{2.72\uparrow}$
NeMo-12B-Instruct																
English	52.56	63.85	70.51	65.64	51.79	49.23	61.03	52.56	38.97	23.08	53.59	67.44	54.10	51.54	55.36	54.18
French	52.05	57.69	66.41	64.36	51.54	48.46	60.77	57.18	57.18	56.67	55.13	59.74	54.10	52.31$_{0.77\uparrow}$	59.12$_{3.76\uparrow}$	57.02$_{2.84\uparrow}$
Chinese	47.95	57.95	63.33	63.85	50.51	47.18	59.49	52.31	56.41	57.18	54.62	61.28	62.82	49.49$_{2.05\downarrow}$	59.66$_{4.30\uparrow}$	56.53$_{2.35\uparrow}$
Japanese	48.21	53.08	60.77	64.10	51.28	47.44	58.46	52.31	56.92	64.36	56.67	58.72	53.59	49.81$_{1.73\downarrow}$	58.52$_{3.16\uparrow}$	55.84$_{1.66\uparrow}$
Multilingual	51.54	56.67	67.18	61.28	52.05	49.74	61.28	51.28	54.36	57.69	56.67	58.72	59.49	51.15$_{0.39\downarrow}$	59.26$_{3.90\uparrow}$	56.77$_{2.59\uparrow}$
Native	57.44	57.69	70.00	65.64	57.69	66.92	60.77	58.72	55.13	64.36	64.87	65.90	62.82	60.19$_{8.65\uparrow}$	63.02$_{7.66\uparrow}$	62.15$_{7.97\uparrow}$
Aya-Expanse-8B																
English	53.08	57.44	60.51	66.41	58.46	66.41	57.44	57.18	26.41	44.62	59.74	61.79	60.51	58.78	54.99	56.15
French	55.64	59.23	71.79	63.85	57.69	72.31	64.87	54.10	61.79	65.38	65.64	70.77	65.64	59.94$_{1.16\uparrow}$	65.44$_{10.45\uparrow}$	63.75$_{7.60\uparrow}$
Chinese	55.90	64.62	68.97	63.85	56.15	73.59	61.28	53.08	58.46	59.49	67.69	66.41	61.79	59.68$_{0.90\uparrow}$	63.62$_{8.63\uparrow}$	62.41$_{6.26\uparrow}$
Japanese	59.49	58.72	70.00	66.67	58.21	71.54	63.59	55.13	54.62	61.03	68.46	70.00	64.36	61.09$_{2.31\uparrow}$	64.16$_{9.17\uparrow}$	63.21$_{7.06\uparrow}$
Multilingual	58.46	58.46	69.74	63.33	56.41	69.23	66.15	55.38	61.28	65.64	68.21	71.28	63.08	59.87$_{1.09\uparrow}$	65.24$_{10.25\uparrow}$	63.59$_{7.44\uparrow}$
Native	51.54	63.08	71.54	66.41	56.92	78.97	64.87	59.49	61.03	61.03	67.95	70.51	61.79	61.73$_{2.95\uparrow}$	65.36$_{10.37\uparrow}$	64.24$_{8.09\uparrow}$
GPT3.5-turbo																
English	54.36	50.77	62.31	63.59	54.62	54.10	58.46	51.79	32.82	30.77	56.67	65.13	21.03	53.72	49.06	50.49
French	55.13	56.67	64.62	62.56	58.97	52.05	58.72	56.41	56.41	58.46	59.23	61.79	58.97	55.64$_{1.92\uparrow}$	59.72$_{10.66\uparrow}$	58.46$_{7.97\uparrow}$
Chinese	53.59	61.28	62.56	59.74	55.13	54.36	56.41	56.92	55.90	55.64	56.41	59.23	53.85	55.00$_{1.28\uparrow}$	57.89$_{8.83\uparrow}$	57.00$_{6.51\uparrow}$
Japanese	53.33	55.38	65.90	63.08	58.97	53.08	58.97	55.90	56.15	56.41	55.90	64.36	54.87	55.32$_{1.60\uparrow}$	59.00$_{9.94\uparrow}$	57.87$_{7.38\uparrow}$
Multilingual	52.82	60.00	66.92	59.23	60.00	54.36	60.77	56.41	53.59	56.67	61.54	63.33	59.49	55.90$_{2.18\uparrow}$	60.17$_{11.11\uparrow}$	58.86$_{8.37\uparrow}$
Native	54.62	62.56	64.87	63.59	59.49	58.46	58.21	60.26	54.36	57.95	59.74	64.87	53.85	58.21$_{4.49\uparrow}$	60.11$_{11.05\uparrow}$	59.53$_{9.04\uparrow}$
GPT4o-mini																
English	68.72	27.95	74.36	73.33	62.56	28.46	71.79	65.64	38.21	4.10	53.59	75.64	5.38	56.35	47.15	49.98
French	66.41	58.97	72.82	67.95	60.51	39.23	71.28	68.97	61.28	63.08	72.05	71.03	70.00	58.78$_{2.43\uparrow}$	67.61$_{20.46\uparrow}$	64.89$_{14.91\uparrow}$
Chinese	67.44	58.21	73.08	69.23	58.72	50.26	67.69	68.97	58.72	66.15	70.77	71.79	73.59	61.35$_{5.00\uparrow}$	67.69$_{20.54\uparrow}$	65.74$_{15.76\uparrow}$
Japanese	66.92	52.82	72.56	67.69	60.00	39.23	66.67	65.13	57.95	66.67	68.46	73.85	67.95	57.82$_{1.47\uparrow}$	66.07$_{18.92\uparrow}$	63.53$_{13.55\uparrow}$
Multilingual	66.41	65.13	72.31	68.72	62.05	64.62	68.97	67.95	65.64	64.10	71.28	73.85	67.69	65.26$_{8.91\uparrow}$	68.63$_{21.48\uparrow}$	67.59$_{17.61\uparrow}$
Native	71.54	70.26	76.15	73.33	65.13	82.82	71.79	67.95	67.95	66.15	76.41	75.64	72.05	71.86$_{15.51\uparrow}$	72.19$_{25.04\uparrow}$	72.09$_{22.11\uparrow}$

Table 13: Accuracies (%) of English, Multilingual, Native all Monolingual ICL modes (French, Chinese and Japanese) and two translation strategies (Transl-Lang→En, Transl-En→Lang) across 13 languages of the XL-WiC dataset. AVG represents the average accuracy of the language set (LRLs, HRLs or All languages). The underlined languages in the table header are LRLs, otherwise HRLs. The subscript indicates the performance increase↑ (or decrease↓) of all other modes compared to the English ICL mode.

McNemar's Test MGSM ICL Mode M1 vs M2 Comparison	Low-Resource Languages χ^2	p-value	Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct	High-Resource Languages χ^2	p-value	Sig. Level	#Both False	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct
Llama3-8B-Instruct														
English vs French	0.85	3.56×10^{-1}		280	78	91	551	0.08	7.84×10^{-1}		300	104	109	1237
English vs Chinese	0.65	4.20×10^{-1}		271	87	99	543	1.09	2.97×10^{-1}		295	109	126	1220
English vs Japanese	2.01	1.57×10^{-1}		278	80	100	542	2.58	1.08×10^{-1}		296	108	134	1212
English vs Multilingual	7.53	6.07×10^{-3}	**	277	81	121	521	1.02	3.12×10^{-1}		302	102	118	1228
English vs Native	2.16	1.41×10^{-1}		276	82	103	539	0.00	1.00×10^{0}		294	110	109	1237
Llama3.1-8B-Instruct														
English vs French	11.75	6.08×10^{-4}	***	311	118	70	501	25.57	4.26×10^{-7}	***	261	192	104	1193
English vs Chinese	17.39	3.04×10^{-5}	***	287	142	79	492	19.63	9.39×10^{-6}	***	263	190	112	1185
English vs Japanese	49.92	1.60×10^{-12}	***	255	174	64	507	14.77	1.22×10^{-4}	***	267	186	118	1179
English vs Multilingual	33.24	8.16×10^{-9}	***	268	161	72	499	24.12	9.03×10^{-7}	***	248	205	116	1181
English vs Native	50.67	1.09×10^{-12}	***	246	183	69	502	27.57	1.52×10^{-7}	***	253	200	107	1190
Qwen2-7B-Instruct														
English vs French	0.40	5.30×10^{-1}		505	58	66	371	0.00	1.00×10^{0}		277	89	88	1296
English vs Chinese	0.53	4.68×10^{-1}		481	82	72	365	3.01	8.30×10^{-2}		266	100	76	1308
English vs Japanese	0.33	5.68×10^{-1}		492	71	79	358	0.08	7.82×10^{-1}		264	102	107	1277
English vs Multilingual	7.36	6.67×10^{-3}	**	451	112	74	363	2.41	1.21×10^{-1}		254	112	89	1295
English vs Native	56.78	4.88×10^{-14}	***	386	177	60	377	20.92	4.80×10^{-6}	***	232	134	68	1316
Qwen2.5-7B-Instruct														
English vs French	0.56	4.56×10^{-1}		344	62	53	541	0.15	7.02×10^{-1}		186	52	57	1455
English vs Chinese	0.21	6.48×10^{-1}		343	63	57	537	1.07	3.02×10^{-1}		164	74	61	1451
English vs Japanese	0.69	4.07×10^{-1}		342	64	54	540	3.20	7.38×10^{-2}		158	80	58	1454
English vs Multilingual	0.00	1.00×10^{0}		342	64	63	531	0.71	3.99×10^{-1}		176	62	52	1460
English vs Native	0.38	5.36×10^{-1}		318	88	79	515	1.76	1.85×10^{-1}		166	72	56	1456
NeMo-12B-Instruct														
English vs French	22.44	2.17×10^{-6}	***	278	152	79	491	8.98	2.73×10^{-3}	**	222	147	99	1282
English vs Chinese	23.24	1.43×10^{-6}	***	271	159	83	487	10.82	1.01×10^{-3}	**	238	131	82	1299
English vs Japanese	17.17	3.41×10^{-5}	***	274	156	90	480	16.32	5.35×10^{-5}	***	211	158	93	1288
English vs Multilingual	16.93	3.87×10^{-5}	***	285	145	82	488	5.66	1.74×10^{-2}	*	229	140	102	1279
English vs Native	29.80	4.79×10^{-8}	***	259	171	83	487	7.05	7.93×10^{-3}	**	235	134	93	1288
Aya-Expanse-8B														
English vs French	0.81	3.67×10^{-1}		611	95	82	212	0.17	6.78×10^{-1}		323	108	101	1218
English vs Chinese	2.70	1.00×10^{-1}		605	101	78	216	0.11	7.44×10^{-1}		317	114	120	1199
English vs Japanese	0.47	4.95×10^{-1}		614	92	82	212	0.31	5.75×10^{-1}		307	124	134	1185
English vs Multilingual	0.20	6.52×10^{-1}		614	92	85	209	0.00	9.51×10^{-1}		296	135	135	1184
English vs Native	4.62	3.16×10^{-2}	*	586	120	88	206	2.47	1.16×10^{-1}		312	119	95	1224
GPT3.5-turbo														
English vs French	1.93	1.64×10^{-1}		455	103	125	317	25.29	4.92×10^{-7}	***	281	235	137	1097
English vs Chinese	0.02	8.98×10^{-1}		438	120	123	319	32.82	1.01×10^{-8}	***	280	236	126	1108
English vs Japanese	0.44	5.09×10^{-1}		449	109	120	322	40.56	1.90×10^{-10}	***	278	238	117	1117
English vs Multilingual	17.81	2.44×10^{-5}	***	398	160	92	350	27.69	1.43×10^{-7}	***	289	227	127	1107
English vs Native	43.05	5.34×10^{-11}	***	374	184	77	365	65.82	4.93×10^{-16}	***	264	252	99	1135
GPT4o-mini														
English vs French	0.24	6.25×10^{-1}		106	36	31	827	0.81	3.68×10^{-1}		136	35	44	1535
English vs Chinese	0.77	3.82×10^{-1}		106	36	28	830	0.05	8.17×10^{-1}		132	39	36	1543
English vs Japanese	1.69	1.93×10^{-1}		106	36	49	809	0.19	6.61×10^{-1}		132	39	44	1535
English vs Multilingual	1.27	2.61×10^{-1}		108	34	45	813	0.01	9.11×10^{-1}		131	40	40	1539
English vs Native	0.30	5.85×10^{-1}		103	39	45	813	1.09	2.95×10^{-1}		139	32	42	1537

Table 14: McNemar's test results of ICL modes on LRL and HRL splits of MGSM dataset. Baseline is the English mode, compared with other Monolingual, Multilingual, and Native modes.

McNemar's Test XCOPA ICL Mode M1 vs M2 Comparison	Low-Resource Languages χ^2	p-value	Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct	High-Resource Languages χ^2	p-value	Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct
Llama3-8B-Instruct														
English vs Italian	274.27	1.33×10^{-61}	***	1246	636	166	1452	8.84	2.95×10^{-3}	**	287	111	70	2032
English vs Chinese	347.11	1.80×10^{-77}	***	1177	705	157	1461	5.85	1.55×10^{-2}	*	288	110	76	2026
English vs Multilingual	366.08	1.33×10^{-81}	***	1163	719	153	1465	15.76	7.21×10^{-5}	***	274	124	68	2034
English vs Native	468.19	7.94×10^{-104}	***	935	947	210	1408	45.38	1.63×10^{-11}	***	240	158	58	2044
Llama3.1-8B-Instruct														
English vs Italian	27.32	1.73×10^{-7}	***	1194	349	223	1734	9.27	2.32×10^{-3}	**	224	102	62	2112
English vs Chinese	74.68	5.53×10^{-18}	***	1105	438	216	1741	0.63	4.28×10^{-1}		241	85	74	2100
English vs Multilingual	157.05	5.00×10^{-36}	***	961	582	225	1732	21.04	4.49×10^{-6}	***	189	137	70	2104
English vs Native	276.51	4.32×10^{-62}	***	723	820	270	1687	46.05	1.16×10^{-11}	***	180	146	50	2124
Qwen2-7B-Instruct														
English vs Italian	8.45	3.65×10^{-3}	**	1084	236	176	2004	0.00	1.00×10^{0}		216	76	77	2131
English vs Chinese	2.59	1.07×10^{-1}		1106	214	181	1999	26.05	3.33×10^{-7}	***	229	63	136	2072
English vs Multilingual	6.11	1.35×10^{-2}	*	1063	257	203	1977	14.73	1.24×10^{-4}	***	193	99	51	2157
English vs Native	40.18	2.31×10^{-10}	***	796	524	337	1843	47.82	4.67×10^{-12}	***	157	135	42	2166
Qwen2.5-7B-Instruct														
English vs Italian	0.03	8.71×10^{-1}		937	299	304	1960	1.82	1.78×10^{-1}		152	79	62	2207
English vs Chinese	1.03	3.10×10^{-1}		990	246	223	2041	0.01	9.30×10^{-1}		167	64	64	2205
English vs Multilingual	0.00	9.68×10^{-1}		931	305	307	1957	4.60	3.20×10^{-2}	*	144	87	60	2209
English vs Native	11.49	6.98×10^{-4}	***	713	523	418	1846	13.65	2.20×10^{-4}	***	130	101	54	2215
NeMo-12B-Instruct														
English vs Italian	0.05	8.30×10^{-1}		1054	267	273	1906	0.06	8.13×10^{-1}		234	78	82	2106
English vs Chinese	0.93	3.35×10^{-1}		1048	273	297	1882	1.06	3.03×10^{-1}		227	85	100	2088
English vs Multilingual	0.72	3.95×10^{-1}		943	378	354	1825	1.22	2.69×10^{-1}		212	100	84	2104
English vs Native	88.46	5.18×10^{-21}	***	654	667	364	1815	23.24	1.43×10^{-6}	***	178	134	65	2123
Aya-Expanse-8B														
English vs Italian	18.11	2.09×10^{-5}	***	2268	303	206	723	28.96	7.39×10^{-8}	***	242	151	70	2037
English vs Chinese	100.08	1.46×10^{-23}	***	2194	377	147	782	1.51	2.19×10^{-1}		250	143	122	1985
English vs Multilingual	637.99	9.13×10^{-141}	***	1714	857	82	847	63.44	1.66×10^{-15}	***	219	174	53	2054
English vs Native	1003.90	2.55×10^{-220}	***	1176	1395	149	780	104.47	1.60×10^{-24}	***	192	201	41	2066
GPT3.5-turbo														
English vs Italian	0.00	1.00×10^{0}		890	390	391	1829	3.89	4.85×10^{-2}	*	213	148	115	2024
English vs Chinese	0.14	7.06×10^{-1}		860	420	432	1788	0.11	7.36×10^{-1}		199	162	155	1984
English vs Multilingual	0.67	4.12×10^{-1}		864	416	441	1779	22.46	2.15×10^{-6}	***	190	171	93	2046
English vs Native	15.10	1.02×10^{-4}	***	655	625	494	1726	39.95	2.61×10^{-10}	***	170	191	85	2054
GPT4o-mini														
English vs Italian	5.19	2.28×10^{-2}	*	529	113	151	2707	2.82	9.33×10^{-2}		57	37	23	2383
English vs Chinese	1.00	3.18×10^{-1}		521	121	105	2753	0.61	4.35×10^{-1}		68	26	33	2373
English vs Multilingual	9.63	1.91×10^{-3}	**	481	161	109	2749	3.32	6.84×10^{-2}		57	37	22	2384
English vs Native	51.49	7.21×10^{-13}	***	348	294	143	2715	0.40	5.25×10^{-1}		60	34	28	2378

Table 15: McNemar's test results of ICL modes on LRL and HRL splits of XCOPA dataset. Baseline is the English mode, compared with other Monolingual, Multilingual, and Native modes.

McNemar's Test XL-WiC ICL Mode M1 vs M2 Comparison	χ^2	p-value	Low-Resource Languages Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct	χ^2	p-value	High-Resource Languages Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct
Llama3-8B-Instruct														
English vs French	1.85	1.74×10^{-1}		483	182	156	739	3.70	5.45×10^{-2}		991	422	367	1730
English vs Chinese	0.00	9.60×10^{-1}		469	196	194	701	1.38	2.41×10^{-1}		1000	413	379	1718
English vs Japanese	3.67	5.53×10^{-2}		438	227	187	708	4.59	3.22×10^{-2}	*	905	508	441	1656
English vs Multilingual	1.89	1.70×10^{-1}		427	238	208	687	0.45	5.00×10^{-1}		917	496	474	1623
English vs Native	13.85	1.98×10^{-4}	***	334	331	241	654	19.84	8.43×10^{-6}	***	856	557	417	1680
Llama3.1-8B-Instruct														
English vs French	1.47	2.26×10^{-1}		641	226	200	493	113.05	2.10×10^{-26}	***	1130	654	321	1405
English vs Chinese	66.13	4.22×10^{-16}	***	563	304	133	560	94.72	2.19×10^{-22}	***	1125	659	349	1377
English vs Japanese	50.57	1.15×10^{-12}	***	555	312	157	536	96.34	9.66×10^{-23}	***	1195	589	296	1430
English vs Multilingual	82.26	1.19×10^{-19}	***	535	332	135	558	94.44	2.52×10^{-22}	***	985	799	454	1272
English vs Native	134.15	5.06×10^{-31}	***	416	451	163	530	197.07	9.10×10^{-45}	***	956	828	346	1380
Qwen2-7B-Instruct														
English vs French	26.64	2.45×10^{-7}	***	526	278	168	588	99.87	1.62×10^{-23}	***	1559	553	266	1132
English vs Chinese	25.96	3.48×10^{-7}	***	578	226	129	627	274.42	1.23×10^{-61}	***	1392	720	213	1185
English vs Japanese	34.50	4.26×10^{-9}	***	463	341	203	553	311.88	8.52×10^{-70}	***	1347	765	212	1186
English vs Multilingual	20.45	6.13×10^{-6}	***	385	419	297	459	468.48	6.86×10^{-104}	***	1070	1042	260	1138
English vs Native	35.09	3.15×10^{-9}	***	436	368	223	533	645.95	1.70×10^{-142}	***	1059	1053	165	1233
Qwen2.5-7B-Instruct														
English vs French	5.71	1.69×10^{-2}	*	563	95	132	770	2.29	1.30×10^{-1}		1028	235	270	1977
English vs Chinese	13.46	2.44×10^{-4}	***	570	88	145	757	1.80	1.80×10^{-1}		959	304	339	1908
English vs Japanese	17.89	2.34×10^{-5}	***	576	82	147	755	5.40	2.02×10^{-2}	*	991	272	330	1917
English vs Multilingual	3.10	7.83×10^{-2}		546	112	141	761	0.30	5.85×10^{-1}		973	290	276	1971
English vs Native	0.45	5.04×10^{-1}		462	196	182	720	25.30	4.91×10^{-7}	***	902	361	237	2010
NeMo-12B-Instruct														
English vs French	0.95	3.31×10^{-1}		686	70	58	746	25.69	4.01×10^{-7}	***	1167	400	268	1675
English vs Chinese	7.17	7.41×10^{-3}	**	705	51	83	721	28.59	8.95×10^{-8}	***	1098	469	318	1625
English vs Japanese	5.08	2.42×10^{-2}	*	703	53	80	724	16.60	4.62×10^{-5}	***	1147	420	309	1634
English vs Multilingual	0.17	6.83×10^{-1}		684	72	78	726	28.68	8.56×10^{-8}	***	1176	391	254	1689
English vs Native	44.12	3.09×10^{-11}	***	485	271	136	668	87.70	7.63×10^{-21}	***	1023	544	275	1668
Aya-Expanse-8B														
English vs French	0.50	4.79×10^{-1}		346	297	279	638	118.02	1.71×10^{-27}	***	829	751	384	1546
English vs Chinese	0.31	5.79×10^{-1}		361	282	268	649	89.50	3.06×10^{-21}	***	919	661	358	1572
English vs Japanese	2.26	1.33×10^{-1}		354	289	253	664	91.35	1.20×10^{-21}	***	855	725	403	1527
English vs Multilingual	0.43	5.12×10^{-1}		337	306	289	628	109.78	1.10×10^{-25}	***	813	767	407	1523
English vs Native	3.20	7.35×10^{-2}		304	339	293	624	133.37	7.51×10^{-31}	***	904	676	312	1618

Table 16: McNemar's test results of ICL modes on LRL and HRL splits of XL-WiC dataset. Baseline is the English mode, compared with other Monolingual, Multilingual, and Native modes.

MGSM CIS	bn	de	en	es	fr	ja	ru	sw	te	th	zh	LRL AVG	HRL AVG	ALL AVG
Llama3-8B-Instruct														
English + CIS-En	64.40	75.20	84.80	78.40	74.00	69.20	74.00	56.80	49.20	73.60	72.40	61.00	75.43	70.18
English + CIS-Fr	66.00	77.20	85.20	80.40	76.40	67.20	75.60	54.00	58.40	68.00	70.80	61.60	76.11	70.84
English + CIS-Ja	66.40	75.60	83.20	78.80	74.80	66.80	77.20	53.20	53.60	72.00	70.80	61.30	75.31	70.22
English + CIS-Zh	63.60	76.80	83.20	77.20	76.40	69.20	77.60	52.40	52.40	68.80	71.60	59.30	76.00	69.93
English + CIS-Multi	65.60	75.20	83.20	78.40	77.20	66.40	76.40	51.60	55.60	69.20	70.40	60.50	75.31	69.93
Llama3.1-8B-Instruct														
English + CIS-En	52.40	70.80	88.40	70.80	75.20	70.40	74.00	67.60	38.40	65.20	73.20	55.90	74.69	67.85
English + CIS-Fr	52.80	74.40	89.20	79.60	76.80	69.20	78.80	60.00	37.60	58.00	76.40	52.10	77.77	68.44
English + CIS-Ja	61.20	76.00	87.60	78.40	75.20	70.80	78.00	66.40	41.20	66.40	75.60	58.80	77.37	70.62
English + CIS-Zh	58.00	72.40	89.60	80.80	76.00	66.00	77.20	69.60	38.80	53.60	76.00	55.00	76.86	68.91
English + CIS-Multi	62.00	74.80	88.80	81.60	78.00	69.20	79.60	68.80	46.40	72.80	78.80	62.50	78.69	72.80
Qwen2-7B-Instruct														
English + CIS-En	54.40	74.00	89.60	82.00	78.80	69.60	79.20	24.80	19.20	73.60	81.20	43.00	79.20	66.04
English + CIS-Fr	55.20	75.20	90.00	84.00	72.80	68.00	80.80	26.40	18.00	74.40	82.00	43.50	78.97	66.07
English + CIS-Ja	56.00	75.20	90.40	78.00	76.80	69.20	79.20	24.80	20.40	74.00	80.00	43.80	78.40	65.82
English + CIS-Zh	55.60	74.80	90.80	79.20	76.80	67.60	80.80	21.60	18.40	75.20	80.40	42.70	78.63	65.56
English + CIS-Multi	54.80	76.40	89.60	82.00	76.80	69.20	80.00	24.40	18.00	73.20	81.20	42.60	79.31	65.96
Qwen2.5-7B-Instruct														
English + CIS-En	75.20	86.40	92.40	88.00	87.60	80.80	88.00	31.60	48.00	82.80	85.20	59.40	86.91	76.91
English + CIS-Fr	75.60	85.20	94.00	89.60	86.00	78.80	87.20	31.60	46.40	84.00	82.80	59.40	86.23	76.47
English + CIS-Ja	76.80	86.40	92.40	90.40	85.60	81.20	86.00	29.60	50.40	83.60	82.00	60.10	86.29	76.76
English + CIS-Zh	78.00	88.40	93.60	89.20	88.00	80.40	90.00	29.20	52.40	84.00	82.80	60.90	87.49	77.82
English + CIS-Multi	76.00	86.40	94.00	90.40	84.80	80.80	86.80	30.00	51.60	80.40	82.80	59.50	86.57	76.73
NeMo-12B-Instruct														
English + CIS-En	61.20	80.00	92.00	82.00	82.40	71.60	82.00	48.40	62.40	70.80	78.00	60.70	81.14	73.71
English + CIS-Fr	64.80	83.20	90.40	84.00	82.80	72.00	84.40	46.40	63.20	71.20	78.00	61.40	82.11	74.58
English + CIS-Ja	67.20	82.80	92.40	81.20	83.60	73.60	84.80	43.20	63.20	67.20	76.80	60.20	82.17	74.18
English + CIS-Zh	62.80	82.00	91.60	80.40	83.20	70.40	86.00	44.40	65.60	69.20	80.40	60.50	82.00	74.18
English + CIS-Multi	72.00	81.60	92.00	84.00	83.60	73.60	86.40	47.20	67.20	73.20	79.20	64.90	82.91	76.36
Aya-Expanse-8B														
English + CIS-En	36.00	76.40	82.40	83.20	74.80	69.20	77.60	24.00	15.60	35.60	70.80	27.80	76.34	58.69
English + CIS-Fr	42.00	72.80	83.60	79.20	73.20	72.00	76.80	20.80	17.20	34.80	72.40	28.70	75.71	58.62
English + CIS-Ja	40.80	76.40	82.00	79.60	74.80	68.80	76.00	23.20	18.00	35.20	73.20	29.30	75.83	58.91
English + CIS-Zh	38.40	74.40	82.00	79.60	75.20	72.00	80.00	20.40	18.40	37.20	72.40	28.60	76.51	59.09
English + CIS-Multi	39.60	76.40	81.60	81.60	73.60	71.60	77.60	22.80	18.80	30.40	73.20	27.90	76.51	58.84

Table 17: Accuracies (%) of CIS modes across 11 languages of the MGSM dataset. AVG represents the average accuracy of the language set (LRLs, HRLs or All languages). The underlined languages in the table header are LRLs, otherwise HRLs. The subscript indicates the performance increase↑ (or decrease↓) of all other modes compared to the English + CIS-En mode.

XCOPA CIS	en	et	ht	id	it	qu	sw	ta	th	tr	vi	zh	LRL AVG	HRL AVG	ALL AVG
Llama3-8B-Instruct															
English + CIS-En	95.40	56.60	16.00	80.20	84.80	18.60	39.00	58.40	69.80	70.80	80.20	87.40	48.37	83.72	63.10
English + CIS-Fr	95.40	57.00	47.00	80.40	85.80	42.20	52.40	57.80	72.40	74.20	80.60	86.60	58.49	84.48	69.32
English + CIS-Ja	95.00	57.20	39.60	82.20	86.60	46.40	56.00	57.00	73.20	74.00	81.40	85.60	58.69	84.68	69.52
English + CIS-Zh	95.00	58.40	35.80	82.00	86.00	43.00	56.80	57.00	73.80	73.60	81.40	87.60	58.03	84.84	69.20
English + CIS-Multi	95.60	58.40	51.00	81.60	86.80	49.00	59.20	56.40	73.60	74.60	80.40	88.00	61.14	85.32	71.22
Llama3.1-8B-Instruct															
English + CIS-En	96.00	64.00	25.00	84.80	88.60	27.60	51.60	62.20	72.80	76.80	85.00	90.00	55.46	87.24	68.70
English + CIS-Fr	95.20	65.80	23.00	85.00	88.20	42.80	53.20	69.80	76.00	78.00	85.20	89.20	59.40	87.12	70.95
English + CIS-Ja	96.40	65.80	53.60	86.60	89.00	46.60	61.40	68.60	77.00	79.20	86.60	88.40	65.66	87.92	74.93
English + CIS-Zh	95.80	65.40	52.00	86.80	88.80	47.40	58.40	68.40	76.00	78.40	85.00	89.00	64.66	87.76	74.28
English + CIS-Multi	96.40	63.20	51.20	86.80	89.80	48.80	59.80	69.20	75.60	80.80	85.40	89.40	64.74	88.64	74.70
Qwen2-7B-Instruct															
English + CIS-En	97.00	62.00	51.40	87.80	90.20	51.00	52.40	56.40	79.00	76.20	84.00	90.20	62.31	88.28	73.13
English + CIS-Fr	97.00	62.60	49.80	87.20	90.20	50.20	54.00	57.20	79.20	74.40	83.20	90.60	62.31	87.88	72.97
English + CIS-Ja	97.00	62.60	51.40	88.40	89.60	50.80	54.40	58.40	80.20	75.00	83.80	91.80	63.09	88.36	73.62
English + CIS-Zh	97.20	60.80	51.00	86.80	88.80	50.60	53.60	57.80	80.20	76.20	83.40	92.80	62.49	88.36	73.27
English + CIS-Multi	97.20	62.20	52.20	87.80	90.80	51.80	52.20	56.80	78.80	74.60	83.60	90.40	62.51	88.16	73.20
Qwen2.5-7B-Instruct															
English + CIS-En	97.00	63.00	56.60	89.40	91.00	50.20	52.40	56.00	83.40	78.20	87.80	94.20	64.20	89.96	74.93
English + CIS-Fr	96.40	63.60	58.80	90.00	93.00	49.00	51.00	56.80	82.20	79.20	87.40	94.00	64.11	90.52	75.12
English + CIS-Ja	96.60	63.60	60.00	90.00	92.60	50.00	48.80	56.00	82.80	78.80	88.20	93.80	64.20	90.36	75.10
English + CIS-Zh	97.20	64.00	59.80	89.80	92.60	50.20	52.00	58.00	84.00	79.20	88.40	93.60	65.20	90.48	75.73
English + CIS-Multi	96.60	64.60	61.20	90.20	93.00	52.00	48.40	59.20	82.20	80.00	87.80	93.60	65.06	90.68	75.73
NeMo-12B-Instruct															
English + CIS-En	96.40	54.40	55.20	79.80	90.80	49.60	54.20	69.80	63.80	70.40	80.00	90.00	61.00	85.48	71.20
English + CIS-Fr	96.00	55.80	57.40	80.20	90.00	49.40	53.80	71.20	61.20	69.60	79.80	88.60	61.23	84.88	71.08
English + CIS-Ja	95.60	58.40	54.60	82.40	91.20	51.20	54.40	72.00	61.40	69.20	80.60	88.20	61.80	85.32	71.60
English + CIS-Zh	95.60	56.40	53.20	82.40	91.40	50.40	54.80	72.20	61.00	71.00	80.00	90.00	61.14	86.08	71.53
English + CIS-Multi	96.20	57.20	56.20	83.40	92.20	50.60	55.40	73.40	61.80	72.80	81.00	90.20	62.23	86.96	72.53
Aya-Expanse-8B															
English + CIS-En	93.80	16.40	8.60	82.80	85.20	1.80	3.20	40.00	17.60	81.40	74.80	74.80	23.20	83.60	48.37
English + CIS-Fr	94.20	27.80	13.00	84.00	87.80	0.60	5.00	47.00	28.20	81.60	79.40	79.40	28.71	85.40	52.33
English + CIS-Ja	94.00	31.60	12.80	85.00	87.40	0.80	5.40	62.00	40.60	81.40	78.20	83.60	33.06	86.28	55.23
English + CIS-Zh	94.80	28.60	12.00	84.80	87.20	0.40	5.40	43.60	21.80	81.60	76.80	83.60	26.94	86.40	51.72
English + CIS-Multi	94.60	36.40	18.80	86.40	89.00	0.80	12.80	49.80	37.00	82.80	79.60	83.60	33.60	87.28	55.97

Table 18: Accuracies (%) of CIS modes across 12 languages of the XCOPA dataset. AVG represents the average accuracy of the language set (LRLs, HRLs or All languages). The underlined languages in the table header are LRLs, otherwise HRLs. The subscript indicates the performance increase↑ (or decrease↓) of all other modes compared to the English + CIS-En mode.

XL-WiC CIS	bg	da	de	en	et	fa	fr	hr	it	ja	ko	nl	zh	LRL AVG	HRL AVG	ALL AVG
Llama3-8B-Instruct																
English + CIS-En	55.13	65.90	61.54	65.64	53.85	64.36	59.23	53.59	52.05	52.82	54.62	56.92	63.59	56.73	59.15	58.40
English + CIS-Fr	56.15	67.18	63.08	64.62	54.62	65.13	60.00	54.10	53.85	52.82	55.64	60.00	60.26	57.50	59.72	59.03
English + CIS-Ja	56.67	67.95	62.05	64.87	54.10	66.67	60.77	55.13	56.67	53.85	53.85	59.23	62.05	58.14	60.14	59.53
English + CIS-Zh	57.44	68.72	63.33	66.15	54.36	65.64	58.97	55.64	54.10	53.33	54.87	60.26	58.97	58.27	59.86	59.37
English + CIS-Multi	56.67	65.90	62.31	64.36	54.62	65.90	60.77	54.10	54.62	51.79	52.31	59.49	61.03	57.82	59.17	58.76
Llama3.1-8B-Instruct																
English + CIS-En	53.08	52.05	62.05	64.62	41.79	44.36	54.36	52.31	31.03	48.46	52.56	54.36	57.95	47.88	53.05	51.46
English + CIS-Fr	55.13	58.97	63.08	64.87	53.08	47.95	60.77	55.13	53.59	50.77	55.38	60.51	58.97	52.82	58.55	56.79
English + CIS-Ja	55.13	60.77	64.87	65.13	53.33	61.79	59.74	53.59	54.62	50.77	53.85	62.05	54.87	55.96	58.52	57.73
English + CIS-Zh	54.62	58.97	64.36	65.64	53.59	58.46	61.28	52.05	55.13	51.28	54.36	61.28	57.95	54.68	58.92	57.61
English + CIS-Multi	55.38	62.56	62.56	64.62	52.31	61.03	61.28	55.38	52.82	51.79	51.03	64.10	58.46	56.03	58.80	57.95
Qwen2-7B-Instruct																
English + CIS-En	39.74	40.26	61.54	66.15	55.38	54.36	61.28	54.10	37.95	8.21	13.85	55.90	0.26	50.90	38.38	42.23
English + CIS-Fr	53.33	43.59	63.85	65.90	52.05	55.64	62.05	53.59	40.26	18.21	15.90	56.41	3.33	53.65	41.05	44.93
English + CIS-Ja	56.41	50.77	62.05	65.64	53.33	61.28	60.26	53.85	43.85	48.46	34.10	60.26	15.13	56.22	48.95	51.18
English + CIS-Zh	56.41	50.00	62.56	65.38	54.87	61.79	61.03	54.10	43.59	37.69	30.77	59.49	14.10	56.79	47.18	50.14
English + CIS-Multi	55.13	46.67	62.82	64.10	52.05	59.49	61.03	53.08	40.26	26.67	20.00	55.64	6.92	54.94	42.68	46.45
Qwen2.5-7B-Instruct																
English + CIS-En	59.49	61.79	72.05	73.33	57.44	60.51	66.67	58.72	60.77	52.56	64.87	74.62	63.59	59.04	65.58	63.57
English + CIS-Fr	55.90	62.56	71.03	72.05	57.18	62.31	64.36	60.77	59.49	57.95	66.67	71.28	64.10	59.04	65.50	63.51
English + CIS-Ja	57.95	62.31	72.05	71.54	58.46	61.28	64.10	59.74	58.72	65.13	64.62	73.59	65.64	59.36	66.41	64.24
English + CIS-Zh	56.92	61.54	72.56	71.28	57.44	61.54	64.36	61.03	58.72	65.13	65.13	71.79	65.64	59.23	66.24	64.08
English + CIS-Multi	57.18	62.31	71.03	72.82	57.95	63.59	65.13	58.72	57.95	64.10	64.87	73.08	65.90	59.36	66.35	64.20
NeMo-12B-Instruct																
English + CIS-En	48.97	62.56	69.74	66.67	51.79	47.95	58.21	49.74	34.10	38.46	52.56	67.44	53.85	49.62	55.95	54.00
English + CIS-Fr	48.72	62.31	69.74	65.90	51.79	48.97	59.23	52.82	42.56	52.82	51.79	62.82	55.13	50.58	58.03	55.74
English + CIS-Ja	48.21	62.05	71.28	66.15	51.03	47.95	58.72	52.31	37.18	57.69	53.85	65.13	54.62	49.87	58.52	55.86
English + CIS-Zh	48.46	60.00	69.49	65.64	51.54	49.74	58.46	50.51	37.18	54.36	53.85	65.13	57.18	50.06	57.92	55.50
English + CIS-Multi	48.46	58.97	69.74	66.15	52.31	47.95	61.28	52.05	39.23	54.10	54.36	65.90	56.15	50.19	58.43	55.90
Aya-Expanse-8B																
English + CIS-En	52.31	55.64	57.44	65.13	56.92	64.62	54.10	57.44	19.49	49.74	54.62	55.38	57.95	57.82	52.17	53.91
English + CIS-Fr	56.92	60.00	64.10	65.13	59.49	73.59	59.74	56.15	38.97	63.33	64.62	63.59	59.74	61.54	59.91	60.41
English + CIS-Ja	55.90	58.21	62.82	65.38	61.28	71.54	54.62	55.38	28.21	64.36	64.10	61.03	58.46	61.03	57.46	58.56
English + CIS-Zh	56.15	57.95	63.08	65.13	60.51	70.77	54.36	54.87	29.23	63.08	64.62	61.03	60.51	60.58	57.66	58.56
English + CIS-Multi	57.95	60.77	64.36	65.64	59.49	74.36	56.41	57.18	39.49	62.31	65.64	64.87	58.21	62.24	59.74	60.51

Table 19: Accuracies (%) of CIS modes across 13 languages of the XL-WiC dataset. AVG represents the average accuracy of the language set (LRLs, HRLs or All languages). The underlined languages in the table header are LRLs, otherwise HRLs. The subscript indicates the performance increase↑ (or decrease↓) of all other modes compared to the English + CIS-En mode.

McNemar's Test MGSM CIS Mode M1 vs M2 Comparison	Low-Resource Languages χ^2	p-value	Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct	High-Resource Languages χ^2	p-value	Sig. Level	#Both False	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct
Llama3-8B-Instruct														
English + CIS-En vs English + CIS-Zh	1.57	2.10E-01		317	73	90	520	0.47	4.93E-01		339	91	81	1239
English + CIS-En vs English + CIS-Fr	0.16	6.85E-01		311	79	73	537	0.60	4.39E-01		323	107	95	1225
English + CIS-En vs English + CIS-Ja	0.03	8.72E-01		311	79	76	534	0.01	9.40E-01		343	87	89	1231
English + CIS-En vs English + CIS-Multi	0.08	7.72E-01		297	93	98	512	0.01	9.41E-01		341	89	91	1229
Multilingual + CIS-Multi vs English + CIS-Multi	0.06	8.00E-01		327	72	68	533	0.16	6.93E-01		355	83	77	1235
Llama3.1-8B-Instruct														
English + CIS-En vs English + CIS-Zh	0.27	6.02E-01		328	113	122	437	5.35	2.08E-02	*	296	147	109	1198
English + CIS-En vs English + CIS-Fr	5.90	1.51E-02	*	344	97	135	424	10.48	1.21E-03	**	282	161	107	1200
English + CIS-En vs English + CIS-Ja	3.79	5.16E-02		323	118	89	470	7.69	5.54E-03	**	282	161	114	1193
English + CIS-En vs English + CIS-Multi	19.20	1.17E-05	***	298	143	77	482	18.31	1.88E-05	***	278	165	95	1212
Multilingual + CIS-Multi vs English + CIS-Multi	18.27	1.91E-05	***	246	68	129	557	0.07	7.97E-01		250	118	123	1259
Qwen2-7B-Instruct														
English + CIS-En vs English + CIS-Zh	0.03	8.69E-01		498	72	75	355	0.50	4.80E-01		288	76	86	1300
English + CIS-En vs English + CIS-Fr	0.12	7.27E-01		502	68	63	367	0.06	8.06E-01		291	73	77	1309
English + CIS-En vs English + CIS-Ja	0.37	5.42E-01		500	70	62	368	0.96	3.27E-01		283	81	95	1291
English + CIS-En vs English + CIS-Multi	0.07	7.92E-01		507	63	67	363	0.01	9.37E-01		284	80	78	1308
Multilingual + CIS-Multi vs English + CIS-Multi	12.23	4.70E-04	***	464	63	110	363	0.35	5.54E-01		266	87	96	1301
Qwen2.5-7B-Instruct														
English + CIS-En vs English + CIS-Zh	2.06	1.51E-01		351	55	40	554	0.86	3.53E-01		177	52	42	1479
English + CIS-En vs English + CIS-Fr	0.01	9.23E-01		352	54	54	540	1.41	2.36E-01		192	37	49	1472
English + CIS-En vs English + CIS-Ja	0.34	5.62E-01		349	57	50	544	0.97	3.24E-01		183	46	57	1464
English + CIS-En vs English + CIS-Multi	0.00	1.00E+00		347	59	58	536	0.27	6.06E-01		185	44	50	1471
Multilingual + CIS-Multi vs English + CIS-Multi	0.03	8.55E-01		347	61	58	534	0.01	9.28E-01		174	63	61	1452
NeMo-12B-Instruct														
English + CIS-En vs English + CIS-Zh	0.01	9.42E-01		300	93	95	512	1.30	2.55E-01		247	83	68	1352
English + CIS-En vs English + CIS-Fr	0.20	6.57E-01		298	95	88	519	1.46	2.26E-01		234	96	79	1341
English + CIS-En vs English + CIS-Ja	0.08	7.80E-01		293	100	105	502	1.66	1.97E-01		234	96	78	1342
English + CIS-En vs English + CIS-Multi	9.66	1.88E-03	**	285	108	66	541	5.96	1.46E-02	*	239	91	60	1360
Multilingual + CIS-Multi vs English + CIS-Multi	2.31	1.28E-01		283	88	68	561	12.66	3.74E-04	***	242	103	57	1348
Aya-Expanse-8B														
English + CIS-En vs English + CIS-Zh	0.34	5.60E-01		646	76	68	210	0.02	8.78E-01		327	87	84	1252
English + CIS-En vs English + CIS-Fr	0.47	4.91E-01		650	72	63	215	0.56	4.55E-01		330	84	95	1241
English + CIS-En vs English + CIS-Ja	1.22	2.70E-01		634	88	73	205	0.35	5.52E-01		328	86	95	1241
English + CIS-En vs English + CIS-Multi	0.00	1.00E+00		662	60	59	219	0.02	8.77E-01		329	85	82	1254
Multilingual + CIS-Multi vs English + CIS-Multi	6.88	8.71E-03	**	614	71	107	208	0.68	4.09E-01		294	131	117	1208

Table 20: McNemar's test results of ICL modes on LRL and HRL splits of MGSM dataset across 6 MLLMs we use.

McNemar's Test XCOPA CIS Mode M1 vs M2 Comparison	Low-Resource Languages χ^2	p-value	Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct	High-Resource Languages χ^2	p-value	Sig. Level	#Both False	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct
Llama3-8B-Instruct														
English + CIS-En vs English + CIS-Zh	199.24	3.05E-45	***	1353	454	116	1577	8.28	4.00E-03	**	349	58	30	2063
English + CIS-En vs English + CIS-Fr	214.84	1.21E-48	***	1340	467	113	1580	3.34	6.76E-02		349	58	39	2054
English + CIS-En vs English + CIS-Ja	209.37	1.89E-47	***	1317	490	129	1564	4.90	2.69E-02	*	341	66	42	2051
English + CIS-En vs English + CIS-Multi	278.98	1.25E-62	***	1227	580	133	1560	13.34	2.60E-04	***	330	77	37	2056
Multilingual + CIS-Multi vs English + CIS-Multi	0.33	5.64E-01		1099	247	261	1893	0.65	4.19E-01		285	71	82	2062
Llama3.1-8B-Instruct														
English + CIS-En vs English + CIS-Zh	194.42	3.45E-44	***	1133	426	104	1837	1.55	2.13E-01		266	53	40	2141
English + CIS-En vs English + CIS-Fr	39.60	3.12E-10	***	1253	306	168	1773	0.04	8.45E-01		268	51	54	2127
English + CIS-En vs English + CIS-Ja	206.75	7.04E-47	***	1074	485	128	1813	2.44	1.18E-01		258	61	44	2137
English + CIS-En vs English + CIS-Multi	164.28	1.31E-37	***	1077	482	157	1784	10.41	1.25E-03	**	246	73	38	2143
Multilingual + CIS-Multi vs English + CIS-Multi	4.95	2.61E-02	*	956	227	278	2039	0.06	8.13E-01		206	82	78	2134
Qwen2-7B-Instruct														
English + CIS-En vs English + CIS-Zh	0.13	7.15E-01		1222	97	91	2090	0.01	9.07E-01		255	38	36	2171
English + CIS-En vs English + CIS-Fr	0.00	9.48E-01		1200	119	119	2062	1.35	2.45E-01		268	25	35	2172
English + CIS-En vs English + CIS-Ja	2.78	9.53E-02		1184	135	108	2073	0.01	9.09E-01		254	39	37	2170
English + CIS-En vs English + CIS-Multi	0.14	7.09E-01		1186	133	126	2055	0.05	8.15E-01		258	35	38	2169
Multilingual + CIS-Multi vs English + CIS-Multi	2.96	8.55E-02		1099	178	213	2010	9.60	1.95E-03	**	210	49	86	2155
Qwen2.5-7B-Instruct														
English + CIS-En vs English + CIS-Zh	4.03	4.48E-02	*	1092	161	126	2121	2.53	1.12E-01		216	35	22	2227
English + CIS-En vs English + CIS-Fr	0.01	9.10E-01		1098	155	158	2089	1.84	1.75E-01		198	53	39	2210
English + CIS-En vs English + CIS-Ja	0.00	9.57E-01		1078	175	175	2072	0.86	3.53E-01		199	52	42	2207
English + CIS-En vs English + CIS-Multi	2.06	1.51E-01		1034	219	189	2058	3.14	7.63E-02		196	55	37	2212
Multilingual + CIS-Multi vs English + CIS-Multi	2.08	1.49E-01		1008	247	215	2030	0.92	3.38E-01		161	60	72	2207
NeMo-12B-Instruct														
English + CIS-En vs English + CIS-Zh	0.05	8.24E-01		1201	164	159	1976	1.87	1.72E-01		303	60	45	2092
English + CIS-En vs English + CIS-Fr	0.13	7.15E-01		1177	188	180	1955	1.98	1.59E-01		321	42	57	2080
English + CIS-En vs English + CIS-Ja	1.78	1.82E-01		1146	219	191	1944	0.08	7.84E-01		305	58	62	2075
English + CIS-En vs English + CIS-Multi	4.27	3.88E-02	*	1137	228	185	1950	10.54	1.17E-03	**	283	80	43	2094
Multilingual + CIS-Multi vs English + CIS-Multi	0.12	7.24E-01		1069	262	253	1916	0.88	3.47E-01		238	75	88	2099
Aya-Expanse-8B														
English + CIS-En vs English + CIS-Zh	70.71	4.14E-17	***	2503	185	54	758	36.62	1.43E-09	***	310	100	30	2060
English + CIS-En vs English + CIS-Fr	124.96	5.19E-29	***	2444	244	51	761	15.24	9.45E-05	***	324	86	41	2049
English + CIS-En vs English + CIS-Ja	275.84	6.05E-62	***	2301	387	42	770	34.30	4.73E-09	***	313	97	30	2060
English + CIS-En vs English + CIS-Multi	298.12	8.46E-67	***	2285	403	39	773	57.51	3.37E-14	***	292	118	26	2064
Multilingual + CIS-Multi vs English + CIS-Multi	294.90	4.26E-66	***	1795	98	529	1078	9.14	2.50E-03	**	233	49	85	2133

Table 21: McNemar's test results of ICL modes on LRL and HRL splits of XCOPA dataset across 6 MLLMs we use.

McNemar's Test XL-WiC CIS Mode M1 vs M2 Comparison	Low-Resource Languages							High-Resource Languages						
	χ^2	p-value	Sig. Level	#Both Wrong	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct	χ^2	p-value	Sig. Level	#Both False	#M1 Wrong M2 Correct	#M1 Correct M2 Wrong	#Both Correct
Llama3-8B-Instruct														
English + CIS-En vs English + CIS-Zh	3.31	6.90E-02		583	92	68	817	1.69	1.94E-01		1251	183	158	1918
English + CIS-En vs English + CIS-Fr	0.81	3.69E-01		594	81	69	816	1.16	2.81E-01		1269	165	145	1931
English + CIS-En vs English + CIS-Ja	2.25	1.34E-01		566	109	87	798	2.96	8.55E-02		1221	213	178	1898
English + CIS-En vs English + CIS-Multi	1.29	2.57E-01		567	108	91	794	0.00	1.00E+00		1226	208	207	1869
Multilingual + CIS-Multi vs English + CIS-Multi	0.13	7.20E-01		464	186	194	716	4.03	4.46E-02	*	1044	334	389	1743
Llama3.1-8B-Instruct														
English + CIS-En vs English + CIS-Zh	34.03	5.43E-09	***	598	215	109	638	67.56	2.04E-16	***	1234	414	208	1654
English + CIS-En vs English + CIS-Fr	16.94	3.86E-05	***	604	209	132	615	72.71	1.50E-17	***	1298	350	157	1705
English + CIS-En vs English + CIS-Ja	47.64	5.13E-12	***	586	227	101	646	52.87	3.56E-13	***	1207	441	249	1613
English + CIS-En vs English + CIS-Multi	45.23	1.75E-11	***	574	239	112	635	53.72	2.31E-13	***	1171	477	275	1587
Multilingual + CIS-Multi vs English + CIS-Multi	0.97	3.25E-01		509	158	177	716	0.83	3.63E-01		992	426	454	1638
Qwen2-7B-Instruct														
English + CIS-En vs English + CIS-Zh	26.89	2.16E-07	***	566	200	108	686	200.56	1.58E-45	***	1772	391	82	1265
English + CIS-En vs English + CIS-Fr	8.28	4.00E-03	**	638	128	85	709	32.76	1.04E-08	***	1984	179	85	1262
English + CIS-En vs English + CIS-Ja	19.38	1.07E-05	***	551	215	132	662	242.30	1.24E-54	***	1695	468	97	1250
English + CIS-En vs English + CIS-Multi	14.08	1.75E-04	***	598	168	105	689	61.98	3.46E-15	***	1906	257	106	1241
Multilingual + CIS-Multi vs English + CIS-Multi	0.34	5.61E-01		446	243	257	614	392.40	2.48E-87	***	1089	245	923	1253
Qwen2.5-7B-Instruct														
English + CIS-En vs English + CIS-Zh	0.03	8.64E-01		569	70	67	854	1.77	1.83E-01		1060	148	125	2177
English + CIS-En vs English + CIS-Fr	0.01	9.36E-01		561	78	78	843	0.01	9.07E-01		1063	145	148	2154
English + CIS-En vs English + CIS-Ja	0.10	7.48E-01		559	80	75	846	2.30	1.29E-01		1023	185	156	2146
English + CIS-En vs English + CIS-Multi	0.09	7.70E-01		543	96	91	830	2.01	1.57E-01		1026	182	155	2147
Multilingual + CIS-Multi vs English + CIS-Multi	4.75	2.92E-02	*	494	180	140	746	0.24	6.27E-01		883	311	298	2018
NeMo-12B-Instruct														
English + CIS-En vs English + CIS-Zh	0.71	4.01E-01		757	29	22	752	16.69	4.39E-05	***	1373	173	104	1860
English + CIS-En vs English + CIS-Fr	4.17	4.11E-02	*	755	31	16	758	16.67	4.45E-05	***	1354	192	119	1845
English + CIS-En vs English + CIS-Ja	0.20	6.51E-01		762	24	20	754	26.40	2.77E-07	***	1351	195	105	1859
English + CIS-En vs English + CIS-Multi	0.93	3.36E-01		747	39	30	744	23.18	1.47E-06	***	1343	203	116	1848
Multilingual + CIS-Multi vs English + CIS-Multi	10.28	1.35E-03	**	683	54	94	729	9.39	2.18E-03	**	1130	254	329	1797
Aya-Expanse-8B														
English + CIS-En vs English + CIS-Zh	7.64	5.72E-03	**	521	137	94	808	102.12	5.24E-24	***	1402	277	84	1747
English + CIS-En vs English + CIS-Fr	10.90	9.60E-04	***	480	178	120	782	146.30	1.12E-33	***	1292	387	115	1716
English + CIS-En vs English + CIS-Ja	9.03	2.66E-03	**	500	158	108	794	94.02	3.12E-22	***	1404	275	89	1742
English + CIS-En vs English + CIS-Multi	14.59	1.34E-04	***	465	193	124	778	143.32	5.01E-33	***	1301	378	112	1719
Multilingual + CIS-Multi vs English + CIS-Multi	0.80	3.72E-01		417	190	172	781	43.63	3.96E-11	***	965	270	448	1827

Table 22: McNemar's test results of ICL modes on LRL and HRL splits of XL-WiC dataset across 6 MLLMs we use.