Code-Switching In-Context Learning for Cross-Lingual Transfer of Large Language Models

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Abstract

While large language models (LLMs) exhibit strong multilingual abilities, their reliance on English as latent representations creates a *translation barrier*, where reasoning implicitly depends on internal translation into English. When this process fails, performance in non-English languages deteriorates sharply, limiting the inclusiveness of LLM-based applications. Existing cross-lingual in-context learning (X-ICL) methods primarily leverage monolingual demonstrations, often failing to mitigate this barrier and instead reinforcing it. In this work, we introduce code-switching in-context learning (**CSICL**), a simple yet effective prompting strategy that progressively transitions from a target language to English within demonstrations and instruction to facilitate their latent reasoning in English. By explicitly scaffolding the reasoning process through controlled code-switching, **CSICL** acts as an implicit linguistic bridge that enhances cross-lingual alignment and reduces reliance on the translation barrier. We conduct extensive experiments across 4 LLMs, 6 datasets, and 10 languages, spanning both knowledge-intensive and reasoning-oriented domains. Our results demonstrate that **CSICL** consistently outperforms X-ICL baselines, achieving gains of 3.1%p and 1.9%p in both target and unseen languages, respectively. The improvement is even more pronounced in low-resource settings, with gains of 14.7% in target and 5.3% in unseen languages. These findings establish code-switching as a principled and robust approach for overcoming the translation barrier during inference, moving LLMs toward more equitable and effective multilingual systems. [1]

1 Introduction

Large language models (LLMs) have demonstrated remarkable multilingual capabilities, powering diverse tasks such as question answering (Tjuatja et al., 2024), translation (Xu et al., 2024), and reasoning (Shi et al., 2023) across languages. However, recent studies reveal that this competence is far from language-agnostic; LLMs typically rely on English-centric latent representations (Wendler et al., 2024; Zhong et al., 2025). This reliance introduces a *translation barrier*: when an internal translation into English fails, non-English performance drops sharply (Bafna et al., 2025). For example, a model may correctly solve a complex problem in English but misinterpret the same problem in low-resource languages, failing to align crucial entities during the hidden translation step. Such cases highlight that multilingual competence in LLMs remains uneven, thereby limiting the inclusive deployment of these models across diverse linguistic communities around the world.

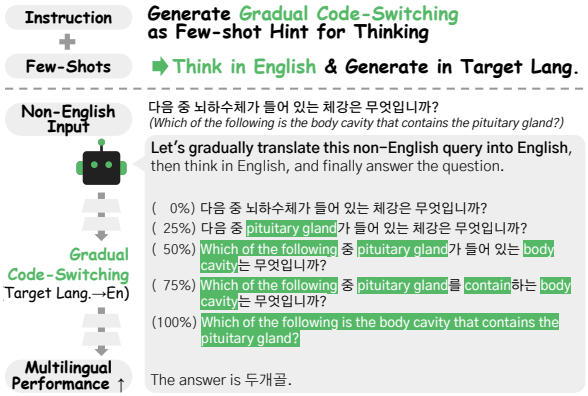


Figure 1: Overview of **CSICL**. We employ 1) gradual code-switching few-shot demonstrations and 2) gradual translation instruction to help the latent process of LLMs for non-English inputs and bypass *translation barrier*.

Cross-lingual in-context learning (X-ICL) has emerged as a practical solution, using demonstrations in high-resource languages (*e.g.*, English) (Lin et al., 2022) to guide performance in low-resource (Cahyawijaya et al., 2024) or unseen (Winata et al., 2022) languages. How-

[1] Code available at https://anonymous.4open.science/r/csicl/.

ever, such demonstrations are typically monolingual, inadvertently reinforcing the latent English representations. Meanwhile, code-switching—the natural alternation between languages—has been shown to benefit cross-lingual transfer in training phases (Wang et al., 2025b; Yoo et al., 2025a; Chai et al., 2025). Despite this potential, code-switching has yet to be systemically explored in X-ICL. This poses a crucial question: *How can we design an inference-time strategy that alleviates the translation barrier and better aligns cross-lingual representations of multilingual LLMs?*

In this paper, we propose code-switching in-context learning (**CSICL**), a prompting strategy that explicitly guides the reasoning process of LLMs through a gradual transition from a target language to English during inference (Figure 1). Specifically, **CSICL** begins in the target language, progressively introduces English representations via code-switching, and converges to a full English equivalent, using chain-of-thought prompting with few-shot demonstrations. This gradual shift acts as a *linguistic bridge*, nudging LLMs to align cross-lingual representations directly, rather than relying solely on latent translation.

We conduct large-scale, rigorous evaluations across 4 multilingual LLMs in 10 languages on 6 datasets spanning diverse tasks and knowledge domains. We observe that **CSICL** consistently outperforms X-ICL baselines, yielding improvements of 3.1%p and 1.9%p in target and unseen languages, respectively. We generalize this to diverse tasks and highlight its effectiveness, particularly in translation and reasoning tasks. These findings position **CSICL** as a robust, promising direction for cross-lingual transfer, moving LLMs closer to more inclusive, end-to-end multilingual systems.

Our contributions are threefold:

- We empirically uncover limitations of current X-ICL approaches in terms of *translation barrier*, where a failure in latent translation of LLMs is propagated to final outputs.
- We propose **CSICL**, a novel code-switching-based prompting strategy that gradually bridges target languages with English representations during inference.
- We conduct a systematic evaluation of **CSICL** across 4 LLMs, 6 tasks, and 10 languages, demonstrating consistent improvements over standard X-ICL baselines.

2 Background

2.1 Code-switching

Code-switching, also known as code-mixing or language alternation, is a common linguistic phenomenon in which a speaker interleaves two or more languages within a single conversational context (Auer, 1998). It occurs in various switching levels: subwords such as at morpheme boundary (*i.e.*, intra-word switching), tag phrases (*i.e.*, tag-switching), words (*i.e.*, intra-sentential switching), and sentences or clauses (*i.e.*, inter-sentential switching). Matrix Language Frame (MLF) model, which distinguishes a grammatically dominant *matrix language* (ML) and an inserted *embedded language* (EL) (Myers-Scotton, 1997), has been widely adopted as a syntactic rule for code-switching. The following examples illustrate code-switching, with variation in the choice of matrix language and embedded language. The sentence originates from Global MMLU (Singh et al., 2025): "*Paper will burn at approximately what temperature in Fahrenheit?*"

(1)

Paper	*will*	***brûler***	*at*	*approximately*	
ML	ML	EL	ML	ML	
quelle	***température***	*in*	*Fahrenheit*	*?*	
EL	EL	ML	ML		

(ML: English, EL: French)

(2)

En	*degrés*	*Fahrenheit,*	*à*	
ML	ML	ML	ML	
approximately	***what***	***temperature***	*le*	
EL	EL	EL	ML	
papier	***burn***	*-t-il*	*?*	
ML	EL	ML		

(ML: French, EL: English)

2.2 In-context learning

In-context learning (ICL) is a paradigm that allows language models to learn tasks given only a few examples in the form of demonstrations (Dong et al., 2024). Brown et al. (2020) investigated a few-shot transfer that concatenates one or more examples as a demonstration, and follow-up studies have explored the selection (Rubin et al., 2022), formatting (Kim et al., 2022), and ordering (Lu et al., 2022) of the demonstration examples. As several tasks require more complex reasoning, Wei et al.

(2022) proposed chain-of-thought (CoT) prompting that generates intermediate reasoning steps between inputs and outputs. Kojima et al. (2022); Wang et al. (2022); Zhang et al. (2023b); Zhou et al. (2023) further introduced zero-shot CoT, highlighting the step-by-step reasoning in LLMs.

3 Code-Switching In-Context Learning

In this paper, we propose code-switching in-context learning (**CSICL**) for cross-lingual transfer of LLMs. Figure 1 illustrates an abstract example of **CSICL**. Given 1) gradual translation instruction and 2) gradual code-switching few-shot demonstrations, **CSICL** facilitates the latent process of LLMs to understand non-English input. The exact system prompts for the demonstrations and the instructions are in Appendix A.2.

Instruction. We instruct LLMs to process non-English inputs by progressively translating them into English using code-switching. Following the few-shot demonstrations, we ask them to

1. Repeat a short, single-sentence instruction that guides a model to gradual translation (*i.e.*, "*Let's gradually translate this non-English query into English, then think in English, and finally answer the question.*");
2. Explicitly show their step-by-step, progressive translation process into English;
3. Provide the final answer in the target language, following the specified format (*e.g.*, "*The answer is . . .* ").

Demonstrations. We employ gradual code-switching as both a few-shot demonstration, which

1. Begins with a query in a target language (*i.e.*, En 0%);
2. Progressively transition to English by leveraging code-switching whose matrix language is the target language and the embedded language is English (*i.e.*, En 25→50→75%);
3. Finally concludes with the full English equivalent (*i.e.*, En 100%).

We randomly sample 5 instances from the test sets as demonstrations and transform them into gradual inter-sentential code-switching from a target language into English. Figure 2 illustrates the two-step

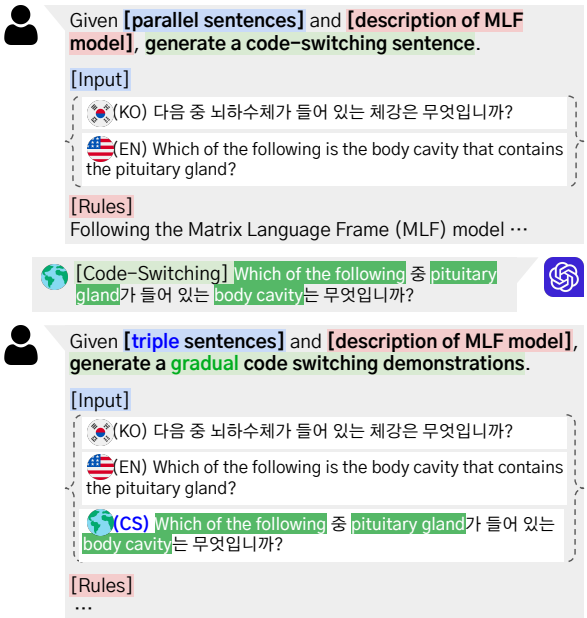


Figure 2: Two-step pipeline to generate gradual code-switching few-shot demonstrations in **CSICL**. We first instruct LLM to convert parallel sentences into code-switching and then generate gradual code-switching following the MLF model.

pipeline to construct these demonstrations in **CSICL**. Following Kim et al. (2025), we first instruct GPT-5 [2] to generate the code-switching sentences given parallel inputs, by providing both a detailed description of the MLF model and five illustrative examples. We then prompt GPT-5 again with the generated output code-switching sentences and parallel sentences to produce gradual code-switching demonstrations. To ground the system prompt, we carefully curate the real-world code-switching examples from Finer (2014).

4 Experiments

4.1 Experimental Setup

4.1.1 Evaluation Setup

Following Lin et al. (2022), we use English prompts with cross-lingual 5-shot demonstrations. The samples used as few-shot demonstrations are excluded from the corresponding test set. For each experiment, we set 3 target languages in total—*i.e.*, French (*high*), Korean (*mid*), Yoruba (*low*)—and report performances in: 1) the target language and 2) random, unseen languages that do not appear in the demonstrations. Evaluating unseen languages is particularly important, as real-world multilin-

[2] Version: `gpt-5-2025-08-07`, accessed via https://platform.openai.com/.

gual systems are often deployed in settings where the test language rarely appears in the training or demonstration phase.

We compare **CSICL** against five conventional X-ICL baselines:

- **Monolingual** few-shot demonstrations in either English or a target language;
- **Parallel** few-shot demonstrations concatenating the target language and English;
- Instructions to **translate** the target language into either English or a random language, given the parallel few-shots (Chai et al., 2025).

For ablations, we additionally employ five baselines to validate the effectiveness of both (gradual) code-switching demonstrations and instructions:

- Inter-sentential **code-switching (CS)** few-shot demonstrations between the English and the target language, controlling a matrix and an embedded language;
- **Gradual code-switching** demonstrations in both directions (*i.e.*, English to the target language and the target language to English);
- Zero-shot **gradual translation** instruction that converts the target language query into English.

4.1.2 Evaluation Models

We use four state-of-the-art multilingual LLMs (*i.e.*, two open and two proprietary models). Model versions and details are stated in Appendix A.1.

- `Qwen3-32B` (Yang et al., 2025);
- `deepseek-chat-v3.1` (DeepSeek-AI et al., 2025);
- `grok-4-fast`;
- `Gemini 2.5 Flash` (Comanici et al., 2025).

4.1.3 Evaluation Datasets

For the experiments in §4.2.1–4.2.3, we construct a balanced set of 36,000 samples by randomly sampling 600 questions per subject category (six in total) and per language (ten in total) from Global MMLU (Singh et al., 2025) for general knowledge evaluation. The languages include English, 3 target languages, and 6 unseen languages spanning resource levels—Chinese, Spanish (*high*); Indonesian, Turkish (*mid*); Swahili, Telugu (*low*).

In §4.2.4, we further conduct an ablation across tasks and knowledge domains using 5 datasets, fixing Spanish as the target and selecting one mid- to high-resource unseen language per dataset (shown in parentheses):

- FLORES+ (Costa-jussà et al., 2024) for machine translation to English (Japanese);
- MedExpQA (Alonso et al., 2024) for domain-specific (*i.e.*, medical) knowledge (French);
- PolyMath (Wang et al., 2025a) for mathematical reasoning (Chinese);
- BLEnD (Myung et al., 2024) for cultural knowledge (Korean);
- MBBQ (Neplenbroek et al., 2024) for social bias (Dutch).

For MBBQ, we randomly select ten samples (five ambiguous contexts and five unambiguous contexts) per template in the MBBQ dataset, totaling 980 samples, due to limited computational resources for processing the full 10k+ instances. For the other task ablation datasets, we employ the entire set for the other datasets. We use accuracy, exact match (EM), and COMET (Rei et al., 2022) as evaluation metrics for multiple-choice questions (Global MMLU, MBBQ), short-answer questions (MedExpQA, PolyMath, BLEnD), and translation (FLORES+), respectively. System prompts for inference and evaluation in each setting and dataset are described in Appendix A.2.

4.1.4 Statistical Significance Testing

Due to limited computational resources, we conduct the following experiments as a single run with a fixed seed. Instead, we apply bootstrap resampling with 2,000 iterations over the evaluation set to rigorously evaluate whether **CSICL** significantly outperforms the baseline systems. In each iteration, we compute the performance difference between **CSICL** and a given baseline and derive a 95% percentile bootstrap confidence interval (CI) from the resulting distribution. A difference is deemed statistically significant if the lower bound of the CI is greater than zero, indicating that **CSICL** consistently outperforms the corresponding baseline. We repeat this analysis against all baselines and mark the results with an asterisk only when **CSICL** achieves statistical significance over every baseline.

Method	X-ICL setting		En	Tgt.*	Unseen Lang.		
	Demonstration	Instruction			High*	Mid*	Low*
Zero-shot learning	✗	✗	88.6	68.6	86.2	62.1	39.4
Few-shot learning	✓ Monolingual (En)	✗	**88.8**	70.8	86.5	62.8	41.2
	✓ Monolingual (Tgt.)	✗	**88.8**	72.0	86.9	62.1	38.7
	✓ Parallel	✗	88.7	72.7	87.1	63.0	41.4
Zero-shot CoT	✗	✓ Translation (Tgt.→En)	**88.8**	74.5	87.4	63.7	42.0
	✗	✓ Translation (Tgt.→Rnd.)	88.6	73.8	87.5	63.8	42.3
CSICL	✓ Gradual CS (Tgt.→En)	✓ Gradual Translation (Tgt.→En)	88.6	**76.8**	**87.8**	**64.9**	**46.0**

Table 1: Experimental results comparing **CSICL** to existing X-ICL baselines. X-ICL setting describes each method in terms of a combination of its few-shot demonstrations and instruction. **CSICL** outperforms X-ICL baselines in both target and unseen languages, yielding stable results in English. Bold and underline denote the best and the second-best results, respectively. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk indicates statistical significance against each and every baseline within the corresponding column.

4.2 Results and Analyses

4.2.1 Main Results

Table 1 reports the results of **CSICL** on Global MMLU. We primarily report experimental results using Qwen 3 in the main text, while the full results for the other three models are stated in Appendix C. **CSICL** outperforms existing X-ICL baselines in both target and unseen languages. Specifically, **CSICL** produces 6.0%p higher performance than monolingual demonstrations in the target language, while the performance gap in English is within 0.2%p. In addition, **CSICL** shows substantial cross-lingual transfer in unseen, low-resource languages (+4.8%p), highlighting its practical need in multilingual scenarios. Interestingly, we observe that monolingual demonstrations in the target language yield higher performance, whereas the benefit diminishes in unseen languages. This contrast highlights a key limitation of monolingual prompting: it overfits the demonstrated language rather than fostering cross-lingual alignment. In contrast, **CSICL** explicitly facilitates this alignment through gradual code-switching, resulting in stronger transfer to unseen settings. We do not observe significant differences in the *out-of-format* ratio, which remains below 0.05% for all X-ICL settings.

Models. Figure 3 displays experimental results of each model with X-ICL approaches in target languages on Global MMLU. All four models achieve similar trends across X-ICL settings, where **CSICL** significantly outperforms existing baselines.

Subject categories. Figure 4 shows experimental results of X-ICL approaches for six subject categories on Global MMLU. **CSICL** significantly surpasses existing baselines across all categories.

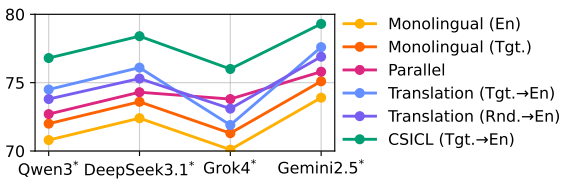


Figure 3: Experimental results of X-ICL approaches in target languages using four different models. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk indicates statistical significance over all baselines.

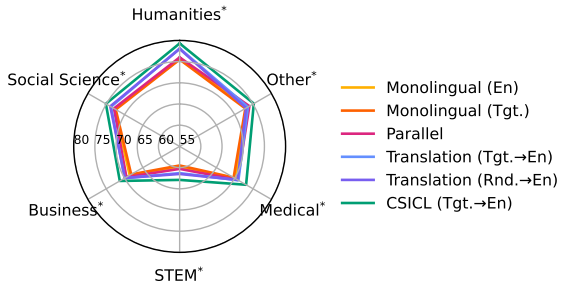
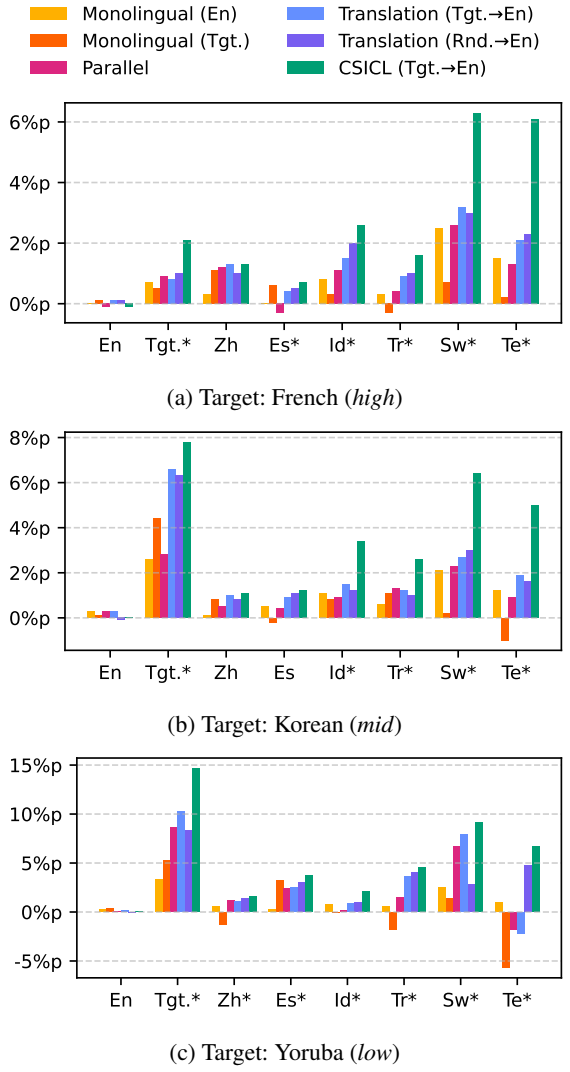


Figure 4: Experimental results of X-ICL approaches for each subject category on Global MMLU. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk indicates statistical significance over all baselines.

Languages. Figure 5 presents performance differences (%p) of each X-ICL setting compared to zero-shot learning, where their target languages are French, Korean, and Yoruba, respectively. **CSICL** outperforms X-ICL baselines, particularly in target languages and mid- to low-resource unseen lan-



(a) Target: French (*high*)

(b) Target: Korean (*mid*)

(c) Target: Yoruba (*low*)

Figure 5: Performance differences (%p) of **CSICL** and X-ICL baselines compared to zero-shot learning setting per a target language. Tgt. and Rnd. denote a target and a random language. Asterisk indicates statistical significance over all baselines.

guages, while English performance remains stable. Interestingly, the benefits of **CSICL** extend beyond script similarity or language family, implying that it fosters language-agnostic cross-lingual alignment rather than relying on superficial linguistic overlap.

4.2.2 Ablation Study

Table 2 shows the experimental results of the ablation study. We observe that both gradual code-switching demonstrations and translation instruction contribute to cross-lingual transfer, by yielding 3.4%p and 3.8% higher accuracy compared to the monolingual baseline. In particular, gradual code-switching consistently achieves higher performances than code-switching (+0.5%p), parallel (+1.5%p), and monolingual demonstrations. Furthermore, transitioning from a target language to English outperforms the reverse direction, supporting our hypothesis that **CSICL** alleviates the translation barrier by scaffolding the latent translation process of LLMs. This asymmetry indicates that LLMs benefit more when demonstrations converge to English representations, aligning with their latent space, rather than diverging away from it. Zero-shot translation and gradual translation instructions yield minimal differences within 0.1%p in the target language, as the model fails to understand the concept of gradual translation and to follow it without explicit demonstrations. Specifically, zero-shot gradual translation instruction often collapses into abrupt translation, where the model outputs two sentences entirely in Korean, followed by three equivalent sentences entirely in English.

4.2.3 CSICL vs. Paraphrasing

CSICL may benefit from using a larger number of sentences, since **CSICL** includes four additional sentences per demonstration. To control for this, we fix the number of sentences per demonstration to five, the same as in **CSICL**, and compare it against monolingual demonstrations. Specifically, for each shot, we add four paraphrased monolingual demonstrations, generated by GPT-5 and then ask the LLMs to solve the task.

Table 3 describes experimental results of **CSICL** and paraphrased demonstrations on Global MMLU, averaged over Qwen 3 and Gemini 2.5. Although paraphrasing provides a marginal improvement in cross-lingual transfer for both target (+0.3%p) and unseen languages (+0.3%p) on average, its effect is limited, and **CSICL** consistently outperforms both baselines. This suggests that the gains of **CSICL** cannot be attributed to a larger demonstration budget alone. Instead, the gradual transition across languages supplies a distinct cross-lingual signal that paraphrasing fails to capture, reinforcing the role of code-switching in aligning multilingual representations.

4.2.4 Task and Domain Knowledge

Table 4 presents experimental results of X-ICL approaches across five additional tasks spanning translation, reasoning, and knowledge-intensive evaluation. In line with earlier results, **CSICL** consistently outperforms existing baselines across settings. Following the descriptions provided in the original papers, we categorize tasks into three types:

- Machine translation (FLORES+);

Method	X-ICL setting		En	Tgt.	Unseen Lang.		
	Demonstration	Instruction			High	Mid	Low
Few-shot learning	✓ CS (En+Tgt.)	✗	88.6	73.6	87.1	62.9	43.3
	✓ CS (Tgt.+En)	✗	88.7	73.7	87.0	62.8	43.1
	✓ Gradual CS (En→Tgt.)	✗	88.7	74.0	87.6	63.8	44.5
	✓ Gradual CS (Tgt.→En)	✗	88.6	74.2	87.7	64.3	45.7
Zero-shot CoT	✗	✓ Gradual Translation (Tgt.→En)	88.7	74.6	87.2	63.8	42.0
CSICL	✓ Gradual CS (En→Tgt.)	✓ Gradual Translation (En→Tgt.)	88.7	75.0	87.6	64.0	45.2
	✓ Gradual CS (Tgt.→En)	✓ Gradual Translation (Tgt.→En)	88.6	**76.8**	**87.8**	**64.9**	**46.0**

Table 2: Ablation results to verify the effectiveness of both (gradual) code-switching demonstrations and translation instruction in **CSICL**. Both components contribute to improved cross-lingual transfer. Bold and underline denote the best and the second-best results, respectively. Tgt. denotes a target language.

X-ICL setting	En	Tgt.*	Unseen Lang.		
			High*	Mid*	Low*
Paraphrasing (En)	**88.9**	71.0	86.6	63.2	41.6
Paraphrasing (Tgt.)	88.8	72.3	87.0	62.6	39.3
CSICL (Tgt.→En)	88.6	**76.8**	**87.8**	**64.9**	**46.0**

Table 3: Experimental results comparing **CSICL** to paraphrased, monolingual demonstrations, keeping the number of sentences per shot. Bold and underline denote the best and the second-best results, respectively. Tgt. denotes a target language. Asterisk indicates statistical significance over all baselines.

- Reasoning-oriented tasks (MedExpQA, PolyMath);
- Knowledge-intensive tasks (BLEnD, MBBQ).

Translation. **CSICL** achieves the largest gains in the translation task—+6.8%p and 3.0%p COMET in the target and the unseen languages, respectively, over monolingual demonstrations. This strong effect is expected, as progressive transition directly scaffolds the latent translation process, aligning the input with English-centric representations. It is noteworthy that **CSICL** is effective even in a purely generative setting.

Reasoning. Beyond translation, **CSICL** also improves reasoning-oriented tasks, with average gains of 5.4%p and 3.8%p of EM over monolingual baselines. We suppose that gradual transitions mitigate representational interference: instead of reasoning entirely in a non-English space, the demonstrations nudge the model to "*think in English,*" where reasoning capabilities are strongest. This highlights the potential of **CSICL** as a lightweight test-time alignment mechanism, complementary to scaling methods such as self-consistency.

Knowledge. For cultural knowledge and social bias, the improvements are modest but still consistent (2.6%p and 1.1%p in the target and the unseen languages, respectively, on average). This indicates that **CSICL** not only facilitates translation-like tasks but also improves general factual consistency across languages.

5 Related Work

5.1 Multilingual Neurons in LLMs

LLMs exhibit language-specific neurons to process multilingual inputs (Zhao et al., 2024). For instance, Schut et al. (2025) empirically demonstrated that LLMs internally translate multilingual inputs into English representations and think in English. This reliance on internal translation introduces a critical vulnerability: *translation barrier*, where a failure in the initial translation stage is propagated to the quality of the final outputs (Bafna et al., 2025). While external machine translation can slightly mitigate this issue (Etxaniz et al., 2024; Intrator et al., 2024), it undermines the goal of using LLMs as seamless, end-to-end multilingual systems. This motivates the exploration of mechanisms that can directly activate cross-lingual capabilities of LLMs without relying on latent English translation.

5.2 Cross-lingual Transfer of LLMs

To bridge this performance gap, cross-lingual transfer has been widely studied (Pallucchini et al., 2025). For example, Tanwar et al. (2023); Li et al. (2024); Lin et al. (2025) investigated X-ICL approaches to better align representations across languages. However, these approaches are primarily

Task type	Translation		Reasoning-oriented						Knowledge-intensive					
			Domain-specific			Math			Cultural			Social Bias		
X-ICL setting	Tgt.*	Uns.*	En	Tgt.*	Uns.*	En	Tgt.*	Uns.*	En	Tgt.*	Uns.*	En	Tgt.*	Uns.
Monolingual (En)	76.6	72.3	**46.4**	38.9	32.1	51.2	49.3	47.4	83.7	77.8	73.2	92.0	88.9	86.3
Monolingual (Tgt.)	75.3	71.6	45.8	38.5	30.3	50.5	49.7	46.1	83.1	78.9	71.5	91.6	89.3	85.8
Parallel	78.1	73.0	46.3	40.2	31.9	**51.4**	49.7	47.7	**83.8**	79.2	72.0	91.5	89.5	86.0
Translation (Tgt.→En)	74.8	72.1	46.1	39.6	32.3	50.8	50.8	48.2	83.3	78.5	71.7	**92.1**	90.1	86.4
Translation (Tgt.→Rnd.)	73.2	73.7	46.3	40.1	32.7	50.3	51.0	47.9	83.6	78.1	72.4	91.9	89.8	**87.3**
CSICL (Tgt.→En)	**83.4**	**75.3**	46.2	**44.4**	**35.2**	50.9	**54.5**	**51.8**	83.5	**81.3**	**74.5**	91.8	**90.5**	87.2

Table 4: Experimental results on 5 diverse tasks and domain knowledge. **CSICL** achieves larger improvements in translation and reasoning tasks. Bold and underline denote the best and the second-best results, respectively. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk denotes statistical significance over all baselines.

based on *monolingual* demonstrations, requiring a more effective signal that is multilingual itself and can bypass the latent translation barrier to activate non-English knowledge during inference.

5.3 Code-switching for Cross-lingual Transfer

Code-switching, which has been studied over decades by the natural language processing community (Winata et al., 2023), is a promising candidate for such a direct signal. Code-switching has shown its efficacy for cross-lingual transfer in various training stages, including pre-training (Wang et al., 2025b), continual pre-training (Yoo et al., 2025a), supervised fine-tuning (SFT) (Lee et al., 2024; Chai et al., 2025), and selective constrained decoding (Li et al., 2025). In particular, Chai et al. (2025) demonstrated that 1) SFT using inter-sentential code-switching data and 2) chain-of-thought prompting, translating a non-English query into a random language and answering in the target language, enhances cross-lingual transfer. Li et al. (2025) introduced probe-guided decoding with an additional classifier to enhance bilingual LLM reasoning with a case study of English-Chinese code-switching.

However, these approaches require substantial additional training resources, while exploration remains limited at the inference level, focusing only on a specific task and domain knowledge. For machine reading comprehension, Kim et al. (2024) provided a passage in English and a QA pair in a target language, which is a form of intra-sentential code-switching. Kim et al. (2025) showcased a case study where Korean-English inter-sentential code-switching can unlock Korean cultural knowledge that remains inaccessible in English queries. Our work, in contrast, introduces a training-free, task- and language-agnostic approach that systemically integrates inter-sentential code-switching into X-ICL. By progressively transitioning from the target language to English within demonstrations and instruction, **CSICL** improves cross-lingual transfer of LLMs during inference. We verify both effectiveness and generality of **CSICL** through extensive experiments across 4 models, 6 datasets, and 10 languages.

6 Conclusion

In this work, we address the *translation barrier* in multilingual LLMs—their over-reliance on English-centric latent representations that often leads to degraded performance in non-English settings. To mitigate this issue, we introduce **CSICL**, a code-switching based prompting strategy that mitigates the *translation barrier* in multilingual LLMs. By gradually transitioning from a target language to English, **CSICL** serves as a linguistic bridge that improves cross-lingual alignment without requiring additional training or resources. We rigorously examine **CSICL** across 4 multilingual LLMs, 6 datasets, and 10 languages. **CSICL** consistently outperforms conventional X-ICL baselines, achieving gains of 3.1%p and 1.9%p in both target and unseen languages, respectively. We demonstrate its pronounced improvements in low-resource settings, with gains of 14.7% in target and 5.3% in unseen languages. Beyond empirical improvements, this paper positions code-switching as a new lens for cross-lingual modeling during LLM inference. Rather than treating language alternation as noise, we frame it as a resource for bridging linguistic gaps, opening a promising view in robust and inclusive multilingual LLM research.

Limitations

In this paper, we focus on inter-sentential code-switching, which can occur at various switching levels. We consider this as a natural first step, and extending the approach to other switching levels is an important direction for future work.

For evaluation, we employ automated metrics (*i.e.*, accuracy, exact match, and COMET) without human evaluation on generation tasks. While human evaluation could provide complementary perspectives, automated metrics enable consistent and large-scale comparisons across multilingual settings, which is central to our study.

We conduct experiments on 10 languages spanning different resource levels. While this set cannot cover all language families, it offers a broad and representative sample that supports the generality of **CSICL**.

In our task- and domain-specific evaluation (§4.2.4), we fix Spanish as the target language and vary the unseen language across datasets due to the limited availability of parallel data in specialized tasks and domains. While this design enables broad coverage of domains, part of the performance differences observed across tasks may stem from the choice of unseen languages rather from the tasks themselves. It reflects the practical challenges of multilingual evaluation and still provides a diverse and informative basis for analysis.

Ethical Considerations

All datasets used in this study are publicly available and employed solely for research purposes, consistent with their intended licenses. **CSICL** aims to improve the multilingual performance of LLMs, with the intended use for both research and practical applications, which is not used for malicious purposes. ChatGPT, Gemini, and Copilot were used for writing and coding assistance.

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Appendix

A Reproducibility Statement

A.1 Evaluation Details

For open-source LLM inference, we use 4 H200 GPUs with 564 GB memory and 4 RTX 8000 GPUs with 188 GB memory. For closed-source LLMs, we access them via OpenRouter[3]. All experiments and sample selections are conducted with a random seed of 42. For reliable reproduction, we use greedy decoding with a temperature of 0.0, if possible. All COMET scores in this paper are COMET-22 (`unbabel/wmt22-comet-da` (Rei et al., 2022).

A.2 System Prompts

A.2.1 Few-shot Demonstrations Generation

Prompt for generating English-Korean code-switching few-shot demonstrations

You are a bilingual rewriting assistant.

[TASK]
• Input : an English sentence (E) and its Korean translation (K)
• Output : the code-switching version of the parallel sentences following Matrix Language Frame (MLF) model
- Replace about 50% percent of words/phrases in E with their Korean equivalents taken from K
- Keep the original English word order and follow English syntax (S-V-O)
- DO NOT add explanations, examples, tags, prefix or extra sentences
- If there is no suitable Korean equivalent, keep the English word

[EXAMPLE]
<English> I ate dinner quickly.
<Korean> 나는 저녁을 빨리 먹었다.
<Code-Switching> I ate 저녁 빨리.

<English> Hana, put the toys in the basket quickly and go home.
<Korean> 하나야, 바구니에 장난감을 빨리 넣고 집에 가자.
<Code-Switching> Hana, put 장난감 in the basket quickly and 집에 가자.

<English> Dad was about to throw away my tooth.
<Korean> 아빠가 내 이빨을 빼려고 했어.
<Code-Switching> 아빠 was about to 뺄래 my 이빨.

<English> I have to wash my hand.
<Korean> 나는 손을 씻어야 해.
<Code-Switching> I have to 닦아 my hand.

<English> Tom thinks Bill likes himself.
<Korean> 톰은 빌이 자기 자신을 좋아한다고 생각한다.
<Code-Switching> Tom thinks that Bill이 자기를 좋아한다.

<English> Tom thinks Bill likes himself.
<Korean> 톰은 빌이 자기 자신을 좋아한다고 생각한다.
<Code-Switching> Tom이 생각하기를 Bill likes himself.

[BEGIN TASK]

Prompt for generating Korean-English code-switching few-shot demonstrations

You are a bilingual rewriting assistant.

[TASK]
• Input : an English sentence (E) and its Korean translation (K)
• Output : the code-switching version of the parallel sentences following Matrix Language Frame (MLF) model
- Replace about 50% percent of words/phrases in K with their English equivalents taken from E
- Keep the original English word order and follow Korean syntax (S-O-V)
- DO NOT add explanations, examples, tags, prefix or extra sentences
- If there is no suitable English equivalent, keep the Korean word

[EXAMPLE]
<English> Meena, put all the toys in the basket quickly, and go home.
<Korean> 미나야, 바구니에 장난감을 다 넣고 빨리 집에 가자.
<Code-Switching> Meena, basket 안에다 all the toys를 빨리 put하고 집에 가자.

<English> Last time, by mistake, they did not renew my driver's license at the DMV.
<Korean> 지난 번에 도로교통공단이 내 운전면허증을 실수로 갱신하지 않았어요.
<Code-Switching> 지난번에 motor vehicle department 에서 내 driver's license를 mistake로 갱신하지 않았어요.

<English> They often do a thing like that.
<Korean> 그들이 일을 종종 그렇게 해요.
<Code-Switching> 그들이 일을 often 그렇게 해요.

<English> Tom thinks Bill likes himself.
<Korean> 톰은 빌이 자기 자신을 좋아한다고 생각한다.
<Code-Switching> Tom은 Bill이 himself를 좋아한다고 생각한다.

<English> John wonders what Mary bought yesterday.
<Korean> 존은 메리가 어제 무엇을 샀는지 궁금해한다.
<Code-Switching> John은 Mary가 yesterday 무엇을 샀는지 궁금해한다.

[BEGIN TASK]

Prompt for generating gradual code-switching (En→Ko) few-shot demonstrations

You are a bilingual rewriting assistant.
Your task is to generate five versions of a sentence that gradually transition from English to Korean.

[INPUT]
• One English sentence (E)
• Its Korean translation (K)
• A code-switching version of the sentence (C), where about 50% of English words are replaced by Korean

[3] https://openrouter.ai/

equivalents

[OUTPUT]
Generate a sequence of five sentences showing a smooth progression from English to Korean:
1. English only (100% English, source syntax S-V-O)
2. 75% English + 25% Korean (matrix language: English, embedded language: Korean)
3. 50% English + 50% Korean (matrix language: English, embedded language: Korean)
4. 25% English + 75% Korean (matrix language: English, embedded language: Korean)
5. Korean only (100% Korean, target syntax S-O-V)

[RULES]
Following the Matrix Language Frame (MLF) model,
• Preserve English word order (S-V-O) and syntax until version 5 (full Korean).
• Use Korean equivalents from K when inserting Korean into English sentences.
• Keep the code-switching natural and consistent, not random.
• Do not add explanations, notes, or extra text — output only the five sentences in order.

[EXAMPLES]

EXAMPLE 1
Input:
<English> I ate dinner quickly.
<Korean> 나는 저녁을 빨리 먹었다.
<Code-Switching> I ate 저녁 빨리.

Output:
1. I ate dinner quickly.
2. I ate dinner 빨리.
3. I ate 저녁 빨리.
4. 나는 저녁 빨리 ate.
5. 나는 저녁을 빨리 먹었다.

EXAMPLE 2
Input:
<English> Dad was about to throw away my tooth.
<Korean> 아빠가 내 이빨을 빼려고 했어.
<Code-Switching> 아빠 was about to 뺄래 my 이빨.

Output:
1. Dad was about to throw away my tooth.
2. Dad was about to throw away 내 이빨.
3. 아빠 was about to 뺄래 my 이빨.
4. 아빠 was about to 내 이빨 빼려고 했어.
5. 아빠가 내 이빨을 빼려고 했어.

Example 3
Input:
<English> Tom thinks Bill likes himself.
<Korean> 톰은 빌이 자기 자신을 좋아한다고 생각한다.
<Code-Switching> Tom thinks that Bill이 자기를 좋아한다.

Output:
1. Tom thinks Bill likes himself.
2. Tom thinks Bill likes 자기.
3. Tom thinks that Bill이 자기를 좋아한다.
4. Tom은 Bill이 자기를 좋아한다고 think한다.
5. 톰은 빌이 자기 자신을 좋아한다고 생각한다.

[BEGIN TASK]

Prompt for generating gradual code-switching (Ko→En) few-shot demonstrations

You are a bilingual rewriting assistant.
Your task is to generate five versions of a sentence that gradually transition from Korean to English.

[INPUT]
• One English sentence (E)
• Its Korean translation (K)
• A code-switching version of the sentence (C), where about 50% of Korean words are replaced by English equivalents

[OUTPUT]
Generate a sequence of five sentences showing a smooth progression from Korean to English:
1. Korean only (100% Korean, source syntax S-O-V)
2. 75% Korean + 25% English (matrix language: Korean, embedded language: English)
3. 50% Korean + 50% English (matrix language: Korean, embedded language: English)
4. 25% Korean + 75% English (matrix language: Korean, embedded language: English)
5. Korean only (100% English, target syntax S-V-O)

[RULES]
Following the Matrix Language Frame (MLF) model,
• Preserve English word order (S-O-V) and syntax until version 5 (full English).
• Use Korean equivalents from E when inserting English into Korean sentences.
• Keep the code-switching natural and consistent, not random.
• Do not add explanations, notes, or extra text — output only the five sentences in order.

[EXAMPLES]

EXAMPLE 1
Input:
<Korean> 미나야, 바구니에 장난감을 다 넣고 빨리 집에 가자.
<English> Meena, put all the toys in the basket quickly, and go home.
<Code-Switching> Meena, basket 안에다 all the toys를 빨리 put하고 집에 가자.

Output:
1. 미나야, 바구니에 장난감을 다 넣고 빨리 집에 가자.
2. Meena, 바구니에 장난감을 다 put하고 빨리 집에 가자.
3. Meena, basket 안에다 all the toys를 빨리 put하고 집에 가자.
4. Meena, put all the toys in the basket quickly, 집에 가자.
5. Meena, put all the toys in the basket quickly, and go home.

EXAMPLE 2
Input:
<Korean> 지난 번에 도로교통공단이 내 운전면허증을 실수로 갱신하지 않았어요.
<English> Last time, by mistake, they did not renew my driver's license at the DMV.
<Code-Switching> 지난번에 motor vehicle department에서 내 driver's license를 mistake로 갱신하지 않았어요.

Output:
1. 지난 번에 도로교통공단이 내 운전면허증을 실수로 갱신하지 않았어요.

2. 지난 번에 motor vehicle department가 내 운전면허증을 실수로 갱신하지 않았어요.
3. 지난번에 motor vehicle department에서 내 driver's license를 mistake로 갱신하지 않았어요.
4. Last time, motor vehicle department에서 my driver's license를 mistake로 renew하지 않았어요.
5. Last time, by mistake, they did not renew my driver's license at the DMV.

Example 3
Input:
<Korean> 존은 메리가 어제 무엇을 샀는지 궁금해한다.
<English> John wonders what Mary bought yesterday.
<Code-Switching> John은 Mary가 yesterday 무엇을 샀는지 궁금해한다.

Output:
1. 존은 메리가 어제 무엇을 샀는지 궁금해한다.
2. John은 메리가 yesterday 무엇을 샀는지 궁금해한다.
3. John은 Mary가 yesterday what을 샀는지 궁금해한다.
4. John wonders what Mary가 yesterday 샀는지 궁금해한다.
5. John wonders what Mary bought yesterday.

[BEGIN TASK]

A.2.2 Code-switching In-context Learning

Prompt for `CSICL`

Answer the following questions written in non-English by explicitly showing a step-by-step translation process into English, then provide the final answer.

Core Behaviors

1. Mandatory Opening Self-Instruction
- Always begin with the exact sentence: "Let's gradually translate this non-English query into English, then think in English, and finally answer the question."
2. Gradual Code-Switching Output:
- Show the transformation from the original query to English in 5 steps.
- Each step progressively replaces more non-English words with English until the query is fully natural English.
- End with a clean, natural English rendering of the question.
3. Answer Format:
- End with the final answer in the exact format: "The answer is X", where 'X' is a single uppercase letter of the correct choice (e.g., A, B, C, D).
- No explanations or justifications after the answer.

Unlike hidden scratchpad reasoning, note that the translation and reasoning process must be explicitly output. Keep the structure identical across all responses.

`{Few-shot demonstrations}`

A.2.3 Evaluation Experiments

Prompt for multiple-choice QA experiments

You will be asked to answer a multiple-choice question. Read the following question and choices then select the single best answer.

- Output only the single uppercase letter of the correct choice (e.g., A, B, C, D).
- Do not output anything else: no reasoning, no explanation, no restating the question, no prefixes like "Answer:", no punctuation, spaces, or newlines.

The final output must be exactly one letter.

Prompt for short-answer QA experiments

You will be asked to answer a short-answer question. Read the following question and provide a single answer without any explanations.

- Output only the single answer.
- Do not output anything else: no reasoning, no explanation, no restating the question, no prefixes like "Answer:", no punctuation, spaces, or newlines.

Prompt for machine translation experiments

You will be asked to translate a `{target language}` text. Read the following sentence and translate it into English without any explanations.

- Output only the English equivalent.
- Do not output anything else: no reasoning, no explanation, no restating the question, no prefixes like "Answer:", no punctuation, spaces, or newlines.

A.3 Licenses

All datasets used in this paper are publicly available. Global MMLU (Singh et al., 2025) is released under the `Apache-2.0` license. BLEnD (Myung et al., 2024), FLORES+ (Costa-jussà et al., 2024), and MedExpQA (Alonso et al., 2024) are distributed under the `CC-BY-SA-4.0` and `CC-BY-4.0` licenses, respectively. The licenses of MBBQ (Neplenbroek et al., 2024) and PolyMath (Wang et al., 2025a) are not explicitly specified.

B More Related Work

In this section, we provide further discussions on prior studies related to code-switching.

Code-switching Text Generation. Only a limited number of code-switching corpora and labeled datasets exist for specific language pairs, and code-switching among non-English languages is hardly available (Winata et al., 2023). Hence, the synthetic generation of code-switching has become the primary strategy. Early efforts such as Jayanthi et al. (2021); Rizvi et al. (2021) proposed toolkits for Hindi-English, although they lack generalizability across languages. More recently, prompting LLMs (*i.e.*, GPT-4) has been widely adopted for synthetic data generation (Yoo et al., 2025a,b; Kim et al., 2025; Yang and Chai, 2025). In particular, Yoo et al. (2025a) further provided quantitative and qualitative analyses comparing LLM-generated code-switching text with human bilingual data, showing

that such text largely follows natural switching patterns with one distinctive feature—redundant synonyms appearing in both languages—which may actually help LLMs by providing explicit lexical alignment cues. Therefore, a slight "unnaturalness" of synthetic code-switching may not be a weakness but rather a source of beneficial noise that facilitates multilingual transfer. In addition, Xie et al. (2025) introduced LinguaMaster, a LLM multi-agent collaboration framework specifically designed for controlled code-switching generation.

Code-switching for Multilingual Evaluations. As the multilingual capabilities of LLMs advance, recent benchmarks range from broad NLP tasks (Yang and Chai, 2025; Abdaljalil et al., 2025; Mohamed et al., 2025) to domain-specific evaluations, including translation (Huzaifah et al., 2024; Zhang et al., 2025), dialogue summarization (Suresh et al., 2025), and red-teaming (Song et al., 2025; Yoo et al., 2025b). Despite these efforts, Zhang et al. (2023a) reported that LLMs still struggle with code-switching, sometimes underperforming compared to smaller, fine-tuned systems. This suggests that code-switching remains an unsolved challenge for multilingual evaluation, rather than a solved proxy task.

C Additional Experimental Results

Tables 5, 6, 7, and 8 present experimental results of X-ICL approaches on Global MMLU using Qwen 3, DeepSeek 3.1, Grok 4, and Gemini 2.5.

X-ICL setting	En	Tgt.*	Zh	Es*	Id*	Tr*	Sw*	Te*
Monolingual (En)	88.6	83.5	89.5	83.2	64.8	60.5	44.6	38.2
Monolingual (Tgt.)	**88.7**	83.3	90.3	83.8	64.3	59.9	42.8	36.9
Parallel	88.5	83.7	90.4	82.9	65.1	60.6	44.7	38.0
Translation (Tgt.→En)	**88.7**	83.6	**90.5**	83.6	65.5	61.1	45.3	38.8
Translation (Rnd.→En)	**88.7**	83.8	90.2	83.7	66.0	61.2	45.1	39.0
CSICL (Tgt.→En)	88.5	**84.9**	**90.5**	**83.9**	**66.6**	**61.8**	**48.4**	**42.8**

(a) Target: French (*high*)

X-ICL setting	En	Tgt.*	Zh	Es	Id*	Tr*	Sw*	Te*
Monolingual (En)	**88.9**	75.4	89.3	83.7	65.1	60.8	44.2	37.9
Monolingual (Tgt.)	88.7	77.2	90.0	83.0	64.8	61.3	42.3	35.7
Parallel	**88.9**	75.6	89.7	83.6	64.9	61.5	44.4	37.6
Translation (Tgt.→En)	**88.9**	79.4	90.2	84.1	65.5	61.4	44.8	38.6
Translation (Rnd.→En)	88.5	79.1	90.0	84.3	65.2	61.2	45.1	38.3
CSICL (Tgt.→En)	88.6	**80.6**	**90.3**	**84.4**	**67.4**	**62.8**	**48.5**	**41.7**

(b) Target: Korean (*mid*)

X-ICL setting	En	Tgt.*	Zh*	Es*	Id*	Tr*	Sw*	Te*
Monolingual (En)	88.9	53.5	89.8	83.5	64.8	60.8	44.6	37.7
Monolingual (Tgt.)	**89.0**	55.5	87.9	86.4	63.9	58.4	43.5	31.0
Parallel	88.7	58.8	90.4	85.6	64.2	61.7	48.8	34.9
Translation (Tgt.→En)	88.8	60.5	90.3	85.7	64.9	63.8	50.0	34.5
Translation (Rnd.→En)	88.6	58.5	90.6	86.2	65.0	64.2	44.9	41.4
CSICL (Tgt.→En)	88.7	**64.9**	**90.8**	**86.9**	**66.1**	**64.7**	**51.2**	**43.4**

(c) Target: Yoruba (*low*)

Table 5: Full experimental results comparing **CSICL** to X-ICL baselines using `Qwen3-32B`. Bold and underline denote the best and the second-best results, respectively. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk indicates statistical significance over all baselines.

X-ICL setting	En	Tgt.*	Zh	Es	Id*	Tr*	Sw*	Te*
Monolingual (En)	**89.6**	84.6	91.2	84.3	66.2	61.5	45.3	38.8
Monolingual (Tgt.)	89.5	84.4	91.8	84.9	65.7	61.0	43.6	37.5
Parallel	89.4	84.7	92.0	84.0	66.5	61.7	45.4	38.6
Translation (Tgt.→En)	**89.6**	84.8	92.1	84.8	66.8	62.1	46.0	39.2
Translation (Rnd.→En)	**89.6**	85.0	91.9	84.9	67.2	62.2	45.8	39.3
CSICL (Tgt.→En)	89.4	**86.0**	**92.3**	**85.1**	**68.0**	**62.9**	**49.1**	**43.1**

(a) Target: French (*high*)

X-ICL setting	En	Tgt.*	Zh	Es	Id*	Tr*	Sw*	Te*
Monolingual (En)	**89.8**	77.3	91.0	84.6	66.4	61.8	45.0	38.6
Monolingual (Tgt.)	89.6	79.1	91.6	83.9	66.0	62.3	43.2	36.5
Parallel	**89.8**	77.5	91.4	84.5	66.1	62.5	45.2	38.3
Translation (Tgt.→En)	**89.8**	81.1	91.8	85.0	66.7	62.4	45.6	39.0
Translation (Rnd.→En)	89.4	80.8	91.5	85.1	66.4	62.2	45.9	38.7
CSICL (Tgt.→En)	89.5	**82.4**	**92.0**	**85.3**	**68.6**	**63.6**	**49.2**	**41.7**

(b) Target: Korean (*mid*)

X-ICL setting	En	Tgt.*	Zh	Es*	Id*	Tr	Sw*	Te*
Monolingual (En)	89.8	55.3	91.5	84.7	66.3	61.9	45.2	38.2
Monolingual (Tgt.)	**89.9**	57.3	89.6	87.4	65.5	59.5	44.1	32.0
Parallel	89.7	60.6	92.0	86.6	65.8	62.7	49.3	35.9
Translation (Tgt.→En)	89.8	62.3	91.9	86.7	66.6	64.5	50.5	35.6
Translation (Rnd.→En)	89.6	60.2	92.3	87.2	66.7	65.0	45.4	42.2
CSICL (Tgt.→En)	89.7	**66.7**	**92.5**	**87.8**	**67.7**	**65.4**	**51.6**	**44.2**

(c) Target: Yoruba (*low*)

Table 6: Full experimental results comparing **CSICL** to X-ICL baselines using `DeepSeek-chat-v3.1`. Bold and underline denote the best and the second-best results, respectively. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk indicates statistical significance over all baselines.

X-ICL setting	En	Tgt.*	Zh	Es	Id*	Tr*	Sw*	Te*
Monolingual (En)	**88.3**	83.0	89.8	83.6	65.0	60.3	44.0	37.5
Monolingual (Tgt.)	88.1	82.9	90.5	84.1	64.6	60.6	42.2	36.2
Parallel	88.2	83.3	90.6	83.4	65.2	60.9	44.2	37.2
Translation (Tgt.→En)	**88.3**	83.2	90.7	84.0	65.6	61.3	44.7	37.9
Translation (Rnd.→En)	88.1	83.5	90.4	84.1	65.7	61.3	44.6	38.1
CSICL (Tgt.→En)	88.0	**84.5**	**90.8**	**84.3**	**66.5**	**61.9**	**47.7**	**41.7**

(a) Target: French (*high*)

X-ICL setting	En	Tgt.*	Zh	Es	Id*	Tr*	Sw*	Te*
Monolingual (En)	**88.4**	74.6	89.6	83.9	65.3	60.6	43.7	37.2
Monolingual (Tgt.)	88.2	76.4	90.2	83.2	65.0	61.1	41.9	35.1
Parallel	**88.4**	78.6	89.9	83.8	65.1	61.3	44.0	36.9
Translation (Tgt.→En)	**88.4**	74.8	90.4	84.2	65.7	61.2	44.3	37.8
Translation (Rnd.→En)	88.1	78.3	90.1	84.4	65.4	61.1	44.6	37.5
CSICL (Tgt.→En)	88.2	**79.7**	**90.6**	**84.6**	**67.1**	**62.3**	**47.8**	**40.8**

(b) Target: Korean (*mid*)

X-ICL setting	En	Tgt.*	Zh	Es*	Id*	Tr*	Sw*	Te*
Monolingual (En)	88.4	52.7	90.1	83.8	65.1	60.7	43.9	36.9
Monolingual (Tgt.)	**88.5**	54.6	88.2	86.7	64.2	58.2	42.8	30.2
Parallel	88.2	59.5	90.7	85.9	64.7	61.4	47.9	34.3
Translation (Tgt.→En)	88.3	57.8	90.6	86.0	65.4	63.5	49.1	34.0
Translation (Rnd.→En)	88.1	57.6	90.9	86.5	65.5	63.8	44.0	40.6
CSICL (Tgt.→En)	88.2	**63.7**	**91.0**	**87.0**	**66.5**	**64.2**	**50.3**	**42.5**

(c) Target: Yoruba (*low*)

Table 7: Full experimental results comparing **CSICL** to X-ICL baselines using `grok-4-fast`. Bold and underline denote the best and the second-best results, respectively. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk indicates statistical significance over all baselines.

X-ICL setting	En	Tgt.*	Zh	Es	Id*	Tr*	Sw*	Te*
Monolingual (En)	**90.2**	85.6	91.5	85.1	67.2	62.7	46.1	39.6
Monolingual (Tgt.)	90.0	85.4	92.1	85.7	66.7	62.3	44.3	38.3
Parallel	90.1	85.8	92.2	84.9	67.5	63.0	46.3	39.4
Translation (Tgt.→En)	**90.2**	85.9	92.3	85.6	67.9	63.4	46.9	40.1
Translation (Rnd.→En)	90.1	86.1	92.1	85.7	68.3	63.5	46.8	40.3
CSICL (Tgt.→En)	90.0	**87.3**	**92.5**	**85.9**	**69.2**	**64.1**	**49.9**	**44.3**

(a) Target: French (*high*)

X-ICL setting	En	Tgt.*	Zh	Es*	Id*	Tr*	Sw*	Te*
Monolingual (En)	**90.3**	79.3	91.3	85.5	67.6	63.0	45.8	39.4
Monolingual (Tgt.)	90.1	81.1	91.9	84.8	67.2	63.5	44.0	37.3
Parallel	**90.3**	79.5	91.6	85.4	67.3	63.7	46.0	39.1
Translation (Tgt.→En)	**90.3**	83.0	92.0	85.9	67.9	63.6	46.4	39.9
Translation (Rnd.→En)	90.0	82.7	91.7	86.1	67.6	63.5	46.7	39.6
CSICL (Tgt.→En)	90.1	**84.3**	**92.2**	**86.4**	**69.7**	**64.8**	**50.1**	**42.8**

(b) Target: Korean (*mid*)

X-ICL setting	En	Tgt.*	Zh	Es	Id*	Tr*	Sw*	Te*
Monolingual (En)	90.3	56.8	91.8	85.4	67.4	63.1	46.0	39.0
Monolingual (Tgt.)	**90.4**	58.9	89.8	88.3	66.6	60.8	44.9	31.7
Parallel	90.2	62.1	92.4	87.5	66.9	63.8	50.1	35.6
Translation (Tgt.→En)	90.3	63.9	92.3	87.6	67.7	65.7	51.3	35.3
Translation (Rnd.→En)	90.1	61.8	92.6	88.1	67.8	66.2	46.3	42.0
CSICL (Tgt.→En)	90.2	**66.2**	**92.8**	**88.6**	**68.9**	**66.6**	**52.5**	**44.8**

(c) Target: Yoruba (*low*)

Table 8: Full experimental results comparing **CSICL** to X-ICL baselines using `Gemini 2.5 Flash`. Bold and underline denote the best and the second-best results, respectively. Tgt. and Rnd. denote a target language and a random language, respectively. Asterisk indicates statistical significance over all baselines.