INCLUDE: EVALUATING MULTILINGUAL LANGUAGE UNDERSTANDING WITH REGIONAL KNOWLEDGE

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Paper under double-blind review

ABSTRACT

The performance differential of large language models (LLM) between languages hinders their effective deployment in many regions, inhibiting the potential economic and societal value of generative AI tools in many communities. However, the development of functional LLMs in many languages (*i.e.*, multilingual LLMs) is bottlenecked by the lack of high-quality evaluation resources in languages other than English. Moreover, current practices in multilingual benchmark construction often translate English resources, ignoring the regional and cultural knowledge of the environments in which multilingual systems would be used. In this work, we construct an evaluation suite of 197,243 QA pairs from local exam sources to measure the capabilities of multilingual LLMs in a variety of regional contexts. Our novel resource, **INCLUDE**, is a comprehensive knowledge- and reasoning-centric benchmark across 44 written languages that evaluates multilingual LLMs for performance in the actual language environments where they would be deployed.

1 INTRODUCTION

The rapid advancement of AI technologies underscores the importance of developing LLMs that are proficient across diverse linguistic and cultural contexts, ensuring fair and equitable performance for stakeholders from various language groups. However, the lack of high-quality evaluation benchmarks in many languages discourages practitioners from training multilingual LLMs to meet this challenge. This evaluation gap limits the effective deployment of LLMs for many regions, exacerbates digital divides, and inhibits the economic and societal value of AI tools in many underserved communities.

The source of this gap is the multitude of challenges in evaluating LLMs for multilingual contexts. First, at a meta-level, the majority of benchmarks for LLMs are only in English (Hendrycks et al., 2020, *inter alia*). While non-English benchmarks exist for some tasks (Singh et al., 2024; Aakanksha et al., 2024; Pozzobon et al., 2024), they usually focus on single languages (Li et al., 2023; Koto et al., 2024), specific regions (Adelani et al., 2024; Cañete et al., 2020; Guevara-Rukoz et al., 2020; Cahyawijaya et al., 2022) and (Etxaniz et al., 2024b), or a particular domain (Wang et al., 2024a), ignoring the importance of joint evaluation to trace and unlock the benefits that multilingual capabilities could bring to low-resource languages (Pfeiffer et al., 2022; Üstün et al., 2024; Aryabumi et al., 2024).

Technical challenges also abound due to the manner in which multilingual datasets are often collected. Certain datasets are constructed using manually applied templates, resulting in low prompt and completion diversity (Muennighoff et al., 2022). Many more are composed of translations from high-resource languages (*e.g.*, English; Holtermann et al., 2024; Myung et al., 2024; Lai et al., 2023). These datasets often contain errors (Ponti et al., 2020; Plaza et al., 2024) and create *translationese artifacts* (Vanmassenhove et al., 2021; Hartung et al., 2023; Savoldi et al., 2021; Ji et al., 2023). Most importantly, they do not accurately reflect the regional and cultural contexts captured by different languages (Aakanksha et al., 2024; Awad et al., 2020; Ramezani & Xu, 2023; Singh et al., 2024). As seen in Figure 1 (a) (Regional Knowledge), a legal question posed in English, Russian, or Greek would likely reflect a user located in a different environment, where different laws may apply to respond correctly. Similarly, also seen in Figure 1 (a) (Cultural Knowledge), historical or cultural perspectives on the same topic may differ among the populaces of different regions.

To resolve this gap, we design a pipeline to collect a large multilingual language understanding benchmark (*i.e.*, **INCLUDE**) by collecting regional resources (*e.g.*, educational, professional, and

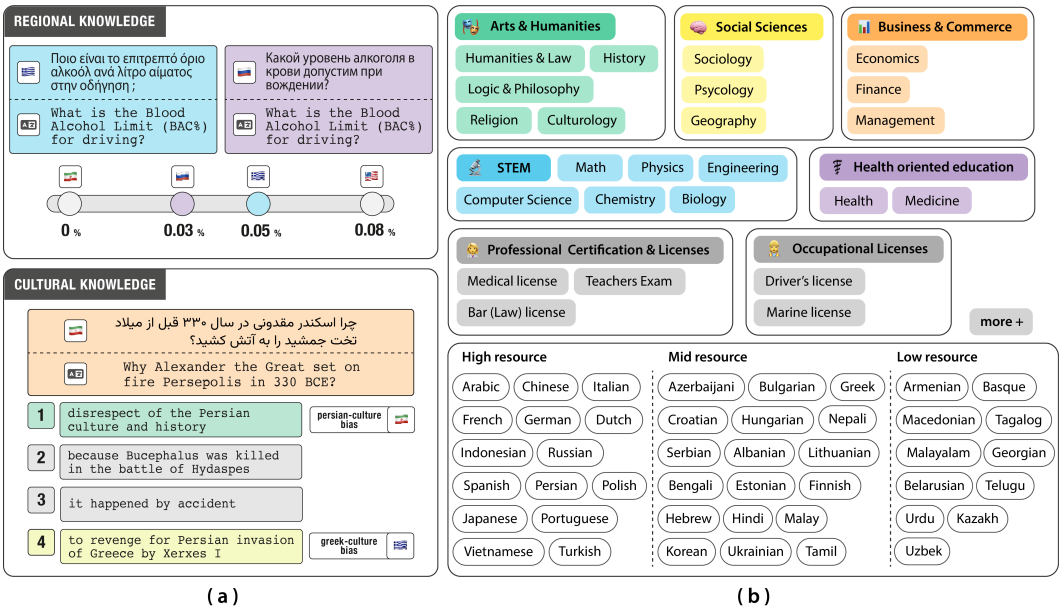

Figure 1: **Overview of INCLUDE.** (a) **Motivation:** Multilingual benchmarks must reflect the cultural and regional knowledge of the language environments in which they would used. (b) **INCLUDE** is a multilingual benchmark compiled from academic, professional, and occupational license examinations reflecting regional and cultural knowledge in 44 languages.

practical tests) that are specific to countries and originally created by native speakers of each country's official languages. This collection avoids *translationese* (Bizzoni et al., 2020) and also captures cultural nuances associated with each language, enabling rigorous evaluation of how state-of-the-art models serve diverse language users around the world.

In our experiments, we sample **INCLUDE** into two subsets for different evaluation budgets and assess an array of closed and open models on these partitions. Our results demonstrate that current models achieve high variance in performance between different languages in **INCLUDE**, and that models often struggle with questions requiring regional knowledge. Further analysis reveals that models score particularly low on languages on which they are not intentionally trained (*i.e.*, limiting regional knowledge acquisition), and that the possibility of transferring global (*i.e.*, English-aligned) perspectives improves performance for less regional topics across languages.

2 PRELIMINARIES: LANGUAGE & KNOWLEDGE

Language availability. Languages are typically characterized as a high, medium, or low resource depending on reported language availability (Joshi et al., 2020), *i.e.*, the amount of available data in a language that is available online. Interestingly, the language availability of documents used for training models (Penedo et al., 2024; Xue, 2020; Conneau et al., 2020; Computer, 2023; Üstün et al., 2024; Singh et al., 2024) differs drastically from the language distribution of non-English LLM benchmarks, with the latter being more scarce. Inspired by this discrepancy, we include 44 languages in our **INCLUDE** benchmark. In Figure 1, we characterize the availability of the included languages based on their reported availability in the mC4 corpus (Xue, 2020), and in Table 4 show further detailed metadata for each language.

Language represents regional knowledge. For LLM-based systems to practically useful, they must enable interaction in the preferred languages of their users and be knowledgeable of the environments of those users. We define *regional knowledge* as the specific information, culture, and practices related to a local environment that is relevant for a user's context. However, LLMs such as GPT-4 tend to exhibit a Western bias (Tao et al., 2024) due to the overrepresentation of Western text in training data (AlKhamissi et al., 2024). In **INCLUDE**, we specifically include questions encompassing the regional and cultural knowledge of a diverse set of high, medium, and low-resource languages.

3 THE INCLUDE BENCHMARK

INCLUDE is a dataset of 197,243 MCQA pairs from 1,926 examinations across 44 languages and 15 scripts. These examinations are collected from local sources in 52 countries, representing a rich array of cultural and regional knowledge. All questions in the dataset are presented in their native languages and scripts. In this section, we describe the data collection procedure for **INCLUDE**, as well as additional categorical labels we assign to each question in the dataset for later analysis.

3.1 DATA COLLECTION

To construct **INCLUDE**, we collect sources of multiple-choice exams in collaboration with native speakers and regional associations. We primarily focused on three types of exams:

Academic Exams: Exams from a variety of subjects (*e.g.*, Humanities, STEM, etc.) at different levels (*e.g.*, middle & high school, university), including country-specific national entrance exams.

Professional Certifications & Licenses: Exams issued by industry-specific regulatory bodies for specialized fields, *e.g.*, licensing exams for areas such as legal and medical practice.

Regional Licenses: Exams administered by regional authorities that assess specific qualifications, such as driving and marine licenses.

We design **INCLUDE** to assess multilingual capabilities that span beyond academic knowledge to cultural and region-specific understanding. Our data collection focuses on license and certification exams that capture regional knowledge of specific countries (in their official languages), and non-translated academic content from the humanities and social sciences to capture cultural knowledge.

From the collected sources, we extract the multiple-choice questions with their corresponding options and correct answers. More specifically, as this data came in different formats (*e.g.*, PDFs, Javascript HTML forms), we use multiple pipelines to extract QA samples from these sources and curate them in a machine-readable manner. The goal of this stage was to automate data extraction and then rely on human evaluation for verification and feature annotation.

Quality Control with Native Speakers. After automatic extraction, we provide native speakers (co-authors in this work) with parsed multiple-choice questions to ensure they were extracted correctly from source documents. In cases of extraction mistakes, annotators performed manual correction of parsed questions and answer options using the original document as a guide. In addition to performing corrections, annotators also filtered out samples that referred to images or tables, and verified that samples that rely on additional context (*e.g.*, reading comprehension) include the reference text in the question field. Finally, annotators also labeled each question with additional exam metadata, such as the language of the MCQ, its topic in both English and the original language, the academic level (if relevant), and the country of origin. In total, we parsed and verified 118,606 samples across 1,926 exam sources, amounting to 60.2% of the total data in **INCLUDE**.

Rounding out the Benchmark. To round out our benchmark, we also consolidate existing datasets with extensive domain coverage in single non-English languages: ArabicMMLU (Koto et al., 2024), ChineseMMLU (Li et al., 2023), TurkishMMLU (Yüksel et al., 2024), PersianMMLU (Ghahroodi et al., 2024) and VNHSGE (Dao et al., 2023), as well as a multilingual benchmark with limited domain coverage across multiple European languages: EXAMS (Hardalov et al., 2020). We repurpose 78,637 samples from these published benchmarks, amounting to 39.8% of the data in **INCLUDE**.

In sum, **INCLUDE** is the largest collection of multilingual exam data to-date. It is composed of 197,243 QA pairs from both novel and existing sources, and covers examinations from more than 1,926 exams in 44 different languages, 15 scripts, and 58 knowledge domains. Figure 1 and Appendix Table 4 summarize the language, domain, and knowledge diversity of the **INCLUDE** benchmark.

3.2 CATEGORIZING KNOWLEDGE

The language breadth of **INCLUDE** provides the opportunity to investigate what factors drive multilingual performance. Consequently, we annotate **INCLUDE** samples with category labels corresponding to factors such as the topic of a question and its region-specificity. Given the prohibitive cost of

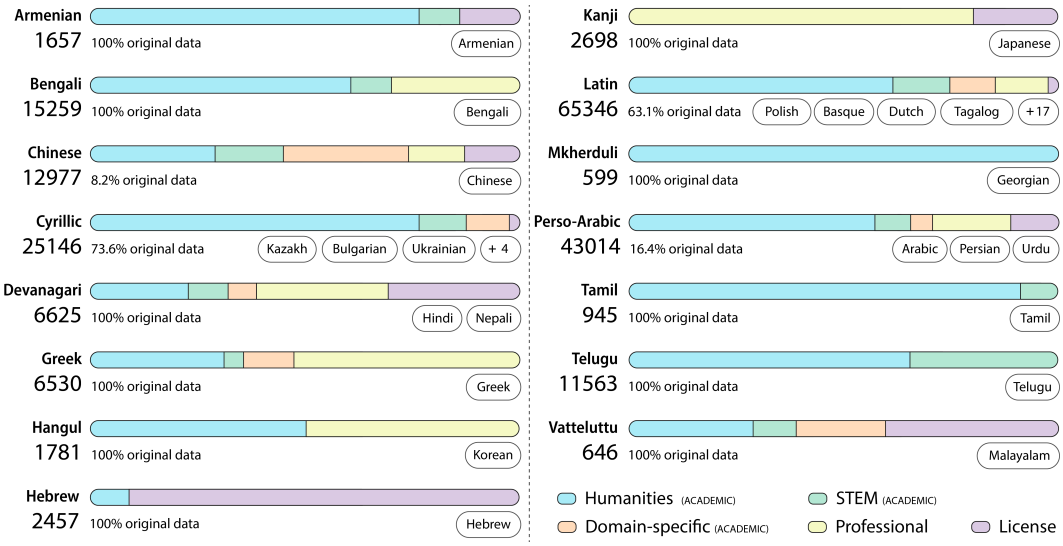

Figure 2: **Overview of the collected data grouped by script.** We depict the languages associated with each script, the total samples in each script, and the percentage of the samples that were collected from new sources that have not been published by the community yet.

performing sample-level annotation, we only perform a coarse annotation by labeling the exam sources of QA pairs, rather than individual samples. We describe our categorization schemes below.

Academic Domain. We manually categorized 1,926 unique exams, following the methodology in Hendrycks et al. (2020). Our categorization follows a two-level taxonomy: a high-level academic area (*e.g.*, Humanities), and particular academic field within this area (*e.g.*, History, Philosophy, Literature).[1] Each exam is categorized based on its title, which indicates its topic (*e.g.*, Greek History) and associated level (*e.g.*, high school, undergraduate, professional certification). Figure 7 provides a breakdown of the number of exam samples per language, organized by this taxonomy.

Regionality. To account for regional knowledge, we categorize exam questions into two major groups: **region-agnostic** and **region-specific** knowledge. Region-agnostic questions do not require knowledge of particular regions (*e.g.*, mathematics, physics), and their answers should remain common regardless of the language in which a question is posed. In total, 34.4% of all questions collected were classified as region-agnostic. In contrast, region-specific questions require knowledge that may depend on a particular cultural or geographical context. This category is further divided into three sub-categories:

Explicitly Regional: A question is classified as *region-explicit* when it pertains to legal, regulatory, or procedural knowledge of regions. Examples include questions about local laws, certifications, clinical guidelines, or licensing requirements (see Figure 1(a)). 18.8% of all questions were *region-explicit*.

Cultural: Language often serves as an implicit marker of culture. For instance, in Figure 1(a), the answer to a question about historical figures in a Greek exam may reflect a different perspective than a similar question posed for a Persian exam. We categorize questions as *cultural* when they pertain to a region's cultural or historical context. This category includes questions for subjects inherently tied to a region's language, history, or social norms. 16.4% of questions were classified as *cultural*.

Implicitly Regional: Finally, the *region-implicit* category is a catch-all for other questions whose answers may depend on a certain degree of regional knowledge understanding. These questions are not explicitly regional or culture-related, but may require regional context to answer correctly. For example, business practices may be different depending on region, even if the underlying theory is common in many places. In total, 30.4% of all questions collected were classified as region-implicit.

Detailed annotation procedures for these categories are described in Appendix A.4, and general statistics about regional labels per academic area and academic field are provided in Figure 7.

[1]This taxonomy is adapted from the *Outline of Academic Disciplines* found on Wikipedia.

4 EXPERIMENTAL SETUP

In this section, we describe our experimental settings for evaluating models on **INCLUDE**.

4.1 DATA SELECTION

The breadth of **INCLUDE** (197,243 QA pairs in 44 languages) makes it amenable to many evaluation use cases, including monolingual evaluation in 44 languages. However, for multilingual evaluation, this same scale is prohibitively expensive for many researchers.[2] Consequently, we curate two subsets of **INCLUDE** for benchmarking multilingual LLMs in different resource settings.

INCLUDE-LITE: This subset uniformly samples 22,635 QA pairs ($\sim$12% of **INCLUDE**) across languages, knowledge tasks, and academic levels. The goal of this subset is to develop a multilingual benchmark with broad language and task coverage. Each language has a maximum of 550 samples, with 500 drawn from domains that correspond to regional knowledge and 50 from STEM subjects.

INCLUDE-TINY: A lightweight subset, uniformly drawn from **INCLUDE-LITE**, designed for rapid assessment of multilingual LLMs with a total of 10,770 samples ($\sim$6% of **INCLUDE**). The upper limit per language is 250 samples and only includes region-specific domains.

For standardization (and alignment with prior benchmarks; Hendrycks et al., 2020), **INCLUDE-LITE** and **INCLUDE-TINY** contain only multiple-choice questions with four answer options. Questions from **INCLUDE** with fewer than four options were omitted during sampling, and questions with more than four options were pruned of options until only four remained. In the following sections, we benchmark models (§5.1) and perform analysis (§5.2-5.3) on **INCLUDE-LITE** and **INCLUDE-TINY**.[3]

4.2 MODELS

We assess **INCLUDE** on GPT-4o (Achiam et al., 2023) as a state-of-the-art multilingual and general-purpose model. We also investigate the role of scaling by benchmarking models that self-report parameters: we compare the larger Aya-23-35B (Aryabumi et al., 2024) 35-billion parameter model and the Qwen2.5-14B (Yang et al., 2024) 14-billion parameter model with Aya-23-8B (Aryabumi et al., 2024) and Qwen2.5-7B (with 8 and 7 billion parameters). Additionally we benchmark Mistral-7B (Jiang et al., 2023), Llama-3-7B (Dubey et al., 2024), Gemma-7B (Team et al., 2024), BLOOMZ-7B (Muennighoff et al., 2022), and XGLM-7.5B (Lin et al., 2021).

We note that some of the models we evaluate such as Mistral and Gemma, do not explicitly claim to support multiple languages, though in practice, they are heavily adopted in multilingual use cases relative to explicitly multilingual models like BLOOMZ (Muennighoff et al., 2022). Furthermore, even reportedly multilingual models (*e.g.*, Aya-23, which supports 23 languages), do not support all 44 languages included in our benchmark. Among the models, XGLM-7.5B has the widest (reported) language coverage, with 23 languages overlapping with our dataset. We evaluate all the mentioned models on the **INCLUDE-TINY** and **INCLUDE-LITE** benchmarks.

We follow the prompting strategy of Hendrycks et al. (2020) and report both 5-shot and zero-shot scores. For the zero-shot setting, we employ a Chain-of-Thought (CoT; Wei et al., 2022) approach by appending the translation of "let's think step by step" to the prompt (Kojima et al., 2022). The maximum generation lengths for the 5-shot and zero-shot CoT configurations are set to 40 and 1024 tokens for the smaller models and to 512 and 1024 tokens for the larger models, respectively.

5 RESULTS & ANALYSIS

5.1 GENERAL PERFORMANCE

Table 1 shows the performance of all models evaluated across the 44 languages in **INCLUDE-LITE**. For larger models, *e.g.*, GPT-4o and Aya-23-35b, we provide results for both 5-shot and zero-shot CoT, while for the remaining models, we report only the 5-shot accuracy.

[2]The cost of evaluating **INCLUDE** using GPT-4o with 5-shot demonstrations exceeded $1000.

[3]We will publicly release both **INCLUDE-LITE** and **INCLUDE-TINY**.

Model	# Langs	INCLUDE-TINY Total Acc.	INCLUDE-TINY Answer Acc.	INCLUDE-TINY Format Errors (%)	INCLUDE-LITE Total Acc.	INCLUDE-LITE Answer Acc.	INCLUDE-LITE Format Errors (%)
GPT-4o	-						
- 5-shot		77.5	**82.7**	6.3	77.3	**83.2**	7.1
- Zero-shot CoT		**78.8**	79.0	0.2	**79.0**	79.2	0.2
Llama-3.1-70B	-						
- 5-shot		70.5	70.5	0.0	70.6	70.6	0.0
- Zero-shot CoT		60.6	67.6	10.4	60.6	67.9	10.9
Aya-expanse-32B	21						
- 5-shot		52.5	56.1	3.9	52.4	55.7	4.3
- Zero-shot CoT		50.6	56.8	10.8	51.4	57.2	10.2
Qwen2.5-14B	22						
- 5-shot		60.9	61.8	1.4	61.4	62.4	1.5
- Zero-shot CoT		46.8	52.8	11.5	47.3	53.1	10.9
Aya-expanse-8B	21	37.2	43.8	18.0	37.1	43.8	17.3
Mistral-7B (v0.3)	-	44.1	44.1	0.0	43.3	43.3	0.0
Mistral-7B-Instruct (v0.3)	-	43.8	44.0	0.3	43.6	43.8	0.4
Gemma-7B	-	55.1	55.1	0.0	54.5	54.5	0.0
Gemma-7B-Instruct	-	39.1	39.1	0.0	38.7	38.7	0.0
Qwen2.5-7B	22	53.8	54.7	1.6	54.1	55.1	1.9
Qwen2.5-7B-Instruct	22	53.2	53.4	0.4	53.8	54.0	0.5
Llama-3.1-8B	-	50.9	50.9	0.0	51.0	51.0	0.0
Llama-3.1-8B-Instruct	-	53.4	53.4	0.0	53.4	53.4	0.0
XGLM-7.5B	23	25.3	26.4	4.0	25.0	26.1	4.1
BLOOM-7.1B	20	25.8	26.6	2.8	25.4	26.1	2.8
BLOOMZ-7.1B	20	27.8	28.8	3.4	27.8	28.8	3.6

Table 1: Results on **INCLUDE-TINY** and **INCLUDE-LITE**. **Total Accuracy** represents the raw accuracy of the model for answering **INCLUDE** questions in each respective subset. **Answer Accuracy** represents the accuracy of the model when only considering samples where an answer is extracted from the model's output in the correct response format. **Formatting Errors (%)** describes the percentage of model responses that are not formatted correctly and so do not output any answer option. We mark these incorrect by default in **Total Accuracy** and do not include them when computing **Answer Accuracy**. **# Langs** reports the number of languages from **INCLUDE** publicly reported to be *intentionally* included in the pretraining data of each model.

Among all models, GPT-4o achieves the highest performance, reaching an accuracy of ∼79% across all domains and examples. We observe that CoT prompting moderately enhances GPT-4o's performance, particularly in Professional and STEM-related exams (Table 2), where the most substantial improvements were seen. In contrast, the smallest gains were observed in exams related to Licenses and the Humanities. Drawing on prior studies that compare CoT and non-CoT prompting strategies across different domains (Sprague et al., 2024), we hypothesize that this observation is due to reasoning skills required in professional examinations (*e.g.*, medicine, law), and computation-heavy subjects in STEM. In contrast, we observe a ∼10% performance drop on average for Aya-expanse-23B, Llama-3.1-70B and Qwen2.5-14B using CoT prompting on **INCLUDE-LITE**, likely because these models are less adapted for mathematical reasoning. GPT-4o and Aya variants also yield more format errors in their answers compared to other models (§5.4).

When comparing smaller models (≤8B parameters), Gemma-7B delivers the best overall performance, with Qwen2.5-7B and Qwen2.5-7B-Instruct closely behind. While Gemma-7B excels in the Humanities and Licenses categories, the Qwen models surpass others in STEM, Applied Sciences, and Professional domains (Table 2). The lowest-performing models in our evaluation are BLOOM, BLOOMZ, and XGLM, which exhibit close to random performance. This poor performance on **INCLUDE** aligns with their results on both MMLU and translated versions of MMLU, as reported in previous studies (Ruan et al., 2024; Lai et al., 2023).

When comparing models of different sizes, we observe that the Aya-23-35B model outperforms the 8B model by ∼17%, while the Qwen2.5-14B model shows a ∼7% improvement over its 7B counterpart on **INCLUDE-LITE**. As the pretraining data remained consistent across the different sizes

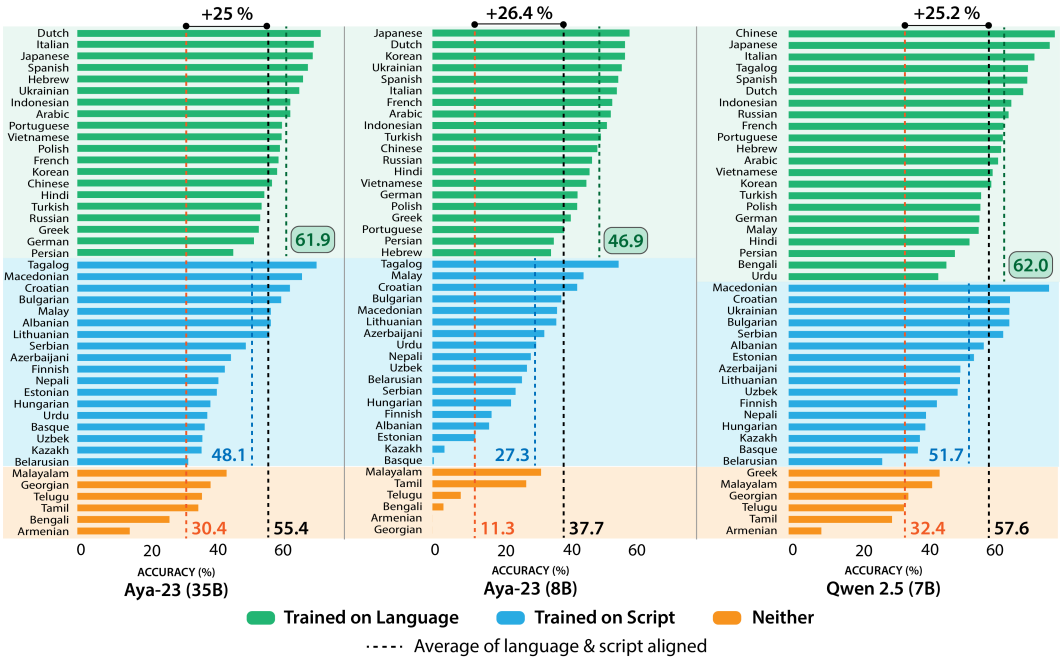

Figure 3: **Performance of models stratified by language.** Results are grouped by whether the language was explicitly included in the pretraining dataset of the model (**Trained on Language**), whether a similar language with the same script was in the pretraining corpus (**Trained on Script**), or whether there was no linguistically similar language in the pretraining corpus (**Neither**). Color dotted lines represent average performance for each category for a particular model. Black dotted lines represent average performance across all script-aligned languages.

within both the Aya-23 and Qwen2.5 model families, we conclude that, with similar training data, increasing model size significantly enhances multilingual capabilities.

Interestingly, we see little benefit to instruction-tuning for improving performance on **INCLUDE-LITE**. Most instruction-tuned models perform slightly worse or on par with their base counterpart, with an outlier performance drop of $\sim$15% for the Gemma-7B-Instruct model. A possible explanation for this gap is that instruction-tuned models may have been fine-tuned predominantly on English data, potentially diminishing multilingual capabilities acquired during pretraining.

Finally, we observe performance on **INCLUDE-TINY** is roughly equivalent to **INCLUDE-LITE** for all models (within 1%), supporting its applicability for more resource-constrained evaluation settings.

5.2 LANGUAGE ANALYSIS

To better understand how LLMs perform on questions in languages seen and unseen during pretraining, we take a deeper look into three open models, *i.e.*, Aya-23-8B, Aya-23-35B, and Qwen2.5-7B, for which we have details surrounding pretraining data (and its associated language distribution). In this analysis, we specifically test three language exposure scenarios: performance on languages the model has been *intentionally*[4] trained on, performance on languages the model was not reported to be trained on but for which the corresponding script was reported to be trained on, and performance on completely unseen languages and scripts during pretraining.

Figure 3 presents the language-stratified performance of these models on **INCLUDE-LITE**. As expected, the models demonstrate better performance on languages that were reported as part of their pretraining data (**Trained on Language**). All models also demonstrate some degree of knowledge transfer to languages they were not trained on but which share the same script as languages in their

[4]We denote *intentionally* in this context to mean that the authors specifically reported this language as being covered in the pretraining corpus of the model.

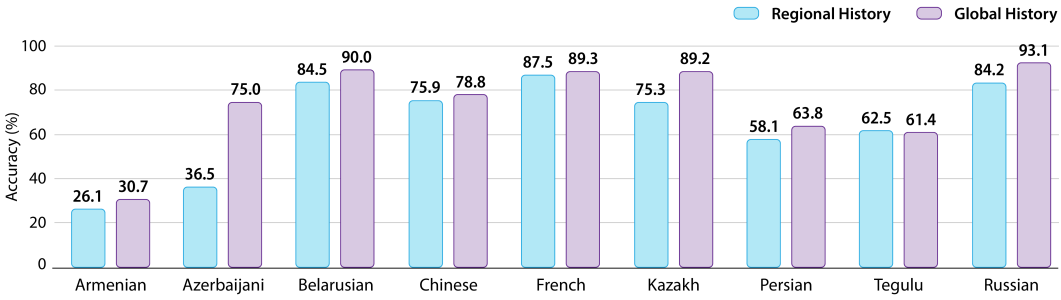

Figure 4: **GPT-4o performance** on regional history exams (*cultural*) and global history exams from that region (*region-implicit*) based on a total of 11,148 questions from **INCLUDE**. In each language (except Telugu), models perform better on the global history exam than the regional history exam.

pretraining data (**Trained on Script**). In this scenario, Aya-23-35B achieves 48.1% accuracy, while Qwen2.5-7B reaches 51.7% accuracy, aligning with previous research that suggests shared scripts enable cross-lingual transfer between languages (Muller et al., 2021; Xhelili et al., 2024). Other factors may also contribute to each model's performance on unseen languages, though, such as cross-lingual transfer across topologically-similar languages. For example, the presence of Turkish data may enhance the model's performance on Azerbaijani (Senel et al., 2024). Pretraining data contamination, where languages that were not intended to be in the pretraining data may still be unintentionally included (Blevins & Zettlemoyer, 2022), may also contribute to these transfer results.

Lastly, we observe that all three models perform poorly on languages whose scripts were not represented in the pretraining corpus (**Neither** in Figure 3). Data contamination is also less of a confounding factor in these cases as language identification is more robust for unique scripts (Kargaran et al., 2023). In these cases, the model often performs worse than random, likely due to not being able to produce responses in the correct format (further details in 5.4).

5.3 REGIONAL & ACADEMIC DOMAIN KNOWLEDGE PERFORMANCE

Using the category labels outlined in Section 3.2, we conduct a stratified analysis of five-shot GPT-4o's ability to answer different types of regional questions in **INCLUDE-LITE**. We first note that overall performance differs strongly between languages. In some languages, the model consistently performs well across all academic domains and regional knowledge types, while in others, it struggles across the board (see Appendix Tables 5, 6, and 7).

However, lower performance in certain languages is often linked to questions requiring regional knowledge (*e.g.*, historical knowledge, professional certifications, medical licenses), suggesting that the model's knowledge about regions varies significantly and that its performance across languages reflects this differential. Among regional categories, in Appendix Figure 6, we see the model performs worst on *cultural* questions, followed by *region-explicit* questions. Professional certification exams in different regions are a particular challenge for GPT-4o (average 68.6%). In Persian, the model's accuracy on certification exams is notably low (43.2%), whereas it performs better on subjects such as Geography and Sociology (over 66%). Similarly, in Greek, GPT-4o achieves an average accuracy of 71.3%, but only 54.1% on medical license questions. Further language performance comparisons across various academic disciplines are shown in Appendix Figure 5.

Despite these findings, we note that performance across regional question types (*e.g.*, region-agnostic, cultural) is not deconfounded from other features such as topical difficulty and academic level. Indeed, we observe that *region-agnostic* questions are among the most challenging as models struggle with the mathematical nature of many STEM topics (Frieder et al., 2023; Borges et al., 2024). On average, subjects such as Mathematics and Chemistry show the lowest average accuracies (Appendix Figure 6). Unfortunately, as the region label of any question depends on its subject, it is naturally confounded with the model's ability in that subject, regardless of whether the subject is regional or not.

History is one of the few fields where we can achieve a more controlled study of regional difference as exams can be divided into two categories: those testing region-specific historical knowledge (*e.g.*, "Armenian history", which we label as *cultural*) and general history taught in a particular region

(*e.g.*, "World History"; *region-implicit*[5]). In Figure 4, we observe that for all languages that have History exams with both *cultural* and *region-implicit* labels (with the exception of Telugu), the model performs better on the general history exams, indicating a lack of *cultural* knowledge necessary to answer questions for more region-specific topics.

Overall, the variance in performance among different regional categories in our results suggests that model performance on **INCLUDE** may not be rooted in across-the-board language comprehension issues, but instead in grasping specialized regional knowledge for different languages.

5.4 CHALLENGES IN MULTILINGUAL EVALUATION

Multilingual LLMs do not generate outputs the same way in all languages. Throughout our experiments, we observed that models did not always follow the exact format primed by the 5-shot examples (**Format Errors** in Table 1), which required generating a longer output length to rectify. To empirically measure the impact of this seemingly minute evaluation design choice, we assess the five-shot performance of GPT-4o on **INCLUDE-LITE** across various decoded output lengths, focusing specifically on its ability to generate a correct response within the first k follow-up tokens (k = 50, 100, 200, and 512). As in our main results, we use the 5-shot prompt template from Hendrycks et al. (2020), without explicitly instructing the model how to generate a correct answers. Instead, the model must induce the format from the provided demonstrations.

Table 9 presents the performance of GPT-4o across the 44 languages of the benchmark, evaluated under four different generation window settings. On average, the model shows a 3.1% performance improvement when increasing the generation length window from 50 to 512 tokens. However, this effect is not uniform; some languages experience significant improvements, such as Uzbek (+17.2%), Armenian (+13.1%), and Malayalam (+12.9%). Many others remain largely unaffected. A manual review and analysis of the generated outputs in languages with the largest gains reveal that the model often generates verbose responses, explaining the context before providing the final answer (*i.e.*, ignoring the formatting in the demonstrations, but reaching the correct response). One possible explanation for these discrepancies is the model's limited ability to leverage in-context learning effectively in certain languages, potentially due to imbalances in language resources during the alignment phase (Zhang et al., 2024c).

Overall, these results demonstrate that standardizing evaluation is a challenge in tasks that may lead to different output patterns (Nayab et al., 2024), which is compounded in multilingual evaluations. In particular, given the incentive to lower generation lengths at test time (to lower inference or API costs), reliable multilingual assessment requires anticipating how models will produce outputs in different languages and scripts, and how evaluation settings might inadvertently affect measures of performance. Specifically, practitioners should be reflective about penalizing models for format errors when assessing capabilities and intentionally probe for format errors, given they may not speak or read the languages being evaluated.

6 RELATED WORK

In recent years, the creation of benchmarks has substantially improved the evaluation of LLMs. Pioneering efforts such as GLUE and SuperGLUE (Wang et al., 2018; 2019) played an important role in advancing tasks related to language understanding. Recent benchmarks, such as MMLU (Hendrycks et al., 2020), HellaSwag (Zellers et al., 2019), ARC (Clark et al., 2018), GSM8K (Cobbe et al., 2021), and BigBench (Srivastava et al., 2022), focus on evaluating models for more complex knowledge comprehension and reasoning. In addition to being used as final evaluations, they are often used to monitor and compare LLM performance during pretraining, rather than more traditional measures such as perplexity (Penedo et al., 2024). However, these benchmarks evaluate models only using English data, limiting their use in the development of multilingual LLMs.

Evaluating multilingual models requires benchmarks that assess models for these same complex abilities across diverse languages. However, initial multilingual benchmarks focus on more basic linguistic abilities (Conneau et al., 2018; Ponti et al., 2020), and collections of such tasks (Liang

[5]We note "World History" as *region-implicit* because the manner in which the subject is taught and evaluated may vary between regions, even if the subject material seems like it should be universal.

et al., 2020; Hu et al., 2020; Ruder et al., 2021; Asai et al., 2023; Ahuja et al., 2023a;b). Furthermore, these benchmarks generally include only a few high-resource languages or are based on translations from high-resource languages, limiting the assessment of regional knowledge comprehension and reasoning capabilities. Finally, similar to English evaluations, multilingual benchmarks have trended toward saturation (Zhang et al., 2024a; Wang et al., 2024b). Although there have been efforts to create language-specific MMLU-like datasets, coverage remains limited to a few languages (Li et al., 2023; Koto et al., 2024; Ghahroodi et al., 2024). Most similar to our proposed effort, the Exams dataset (Hardalov et al., 2020) encompasses questions covering 16 languages across 24 topics collected from elementary and high school science curricula. The Aya dataset (Singh et al., 2024) also includes a sustantial release, covering 513 million data points across 101 languages, including in-language evaluation sets developed by native speakers assessing general performance and safety. However, the Aya dataset is not focused on collecting in-language exams. Our work develops a multilingual benchmark encompassing 44 languages, integrating questions from academic and professional examinations and broadening the evaluation spectrum of multilingual LLMs to include region-specific knowledge.

Finally, a rich body of work has developed benchmarks to assess LLMs for cultural understanding. Arora et al. (2024) evaluate various aspects of culture and language using questions from community forums on 15 topics. Aakanksha et al. (2024) curate a safety dataset that encompasses local nuances. Myung et al. (2024) compile questions about food, sports, holidays, education, and family translated into multiple languages. Synthetic benchmarks, such as NormAd (Rao et al., 2024), generate culturally-rooted stories to measure how well models grasp societal norms. Tools such as CultureBank source cultural descriptions from online platforms such as TikTok (Shi et al., 2024), offering alternative ways to ground cultural benchmarks in dynamic, real-world knowledge. Etxaniz et al. (2024a) analyze the effect of regional vs non-regional knowledge of the LLM using an evaluation dataset that is parallel in English and Basque. Beyond benchmarking, Chiu et al. (2024) proposed a tool that facilitates human-machine collaboration for co-creation of complex datasets, challenging the multicultural understanding and adaptability of LLMs. In contrast to this line of work, our study goes beyond culture as a dimension of regional knowledge, and also assesses LLMs on questions that reflect region-related factual knowledge (*e.g.*, professional standards, law, clinical guidelines).

7 Conclusion

We release **Include**, a comprehensive multilingual evaluation suite designed to assess performance of large language models (LLMs) across a wide range of subjects and languages for a rich array of cultural and regional knowledge. **Include** contains 197,243 MCQA pairs from 1,926 examinations across 44 languages and 15 scripts collected from 52 countries. Overall, our results from evaluating 15 models on **Include** indicate there remains considerable room for model improvement in multilingual regional knowledge understanding and that regional knowledge understanding varies significantly across languages. **Include** offers researchers and developers a novel and valuable benchmark for evaluating and improving the regional understanding abilities of future multilingual models in the language environments where they would be used.

8 Limitations

Our work has several limitations. First, the benchmark spans 44 languages with varying levels of resource availability, leading to different distributions of questions from various academic disciplines across languages. This disparity makes it challenging to perform direct comparisons between performance in disciplines across languages. Additionally, the difficulty of exams may vary not only between languages but also within the same language if exams originate from different sources. However, this limitation is also a reflection of one of the strengths of our benchmark. Questions are sourced from local examinations that reflect the regional and cultural nuances of the environments in which those exams are implemented, which was our motivation for a new evaluation benchmark. Naturally, this precludes exact correspondence between questions across languages. Another practical limitation is that our regional knowledge labels were annotated at the exam topic level, rather than at the individual question level. As a result, questions are classified based on their overarching topic, rather than individual content.

ETHICS STATEMENT

The primary goal of our benchmark is to reduce disparities in performance regional knowledge understanding across languages, addressing the inequities in access to technology and its benefits that often result from these gaps. We have designed the benchmark to reflect a diverse range of linguistic, cultural, and regional contexts, sourcing data from local and region-specific exam materials. Throughout the data collection process, we ensured that no private or sensitive information was included. We only collected data from exams for which there were no license issues. Our benchmark aims to capture and integrate essential cultural knowledge across many languages. We emphasize the importance of local engagement and encourage developers using this benchmark for the evaluation of monolingual models to actively consult with local stakeholders. To promote equitable access to technology and the development of multilingual large language models, we release our benchmark to the community.

REPRODUCIBILITY STATEMENT

We plan to release two subsets, **INCLUDE-LITE** and **INCLUDE-TINY**, alongside the associated documentation and code for data processing and evaluation. These resources will be made publicly available upon acceptance. To mitigate the risk of data contamination during fine-tuning, **INCLUDE** will be released in incremental batches over a period of four months.

Further details regarding experimental settings, including resource utilization, hyperparameters, and baseline configurations, can be found in Section 4 and Appendix A.5, which provide a comprehensive overview of our methodology.

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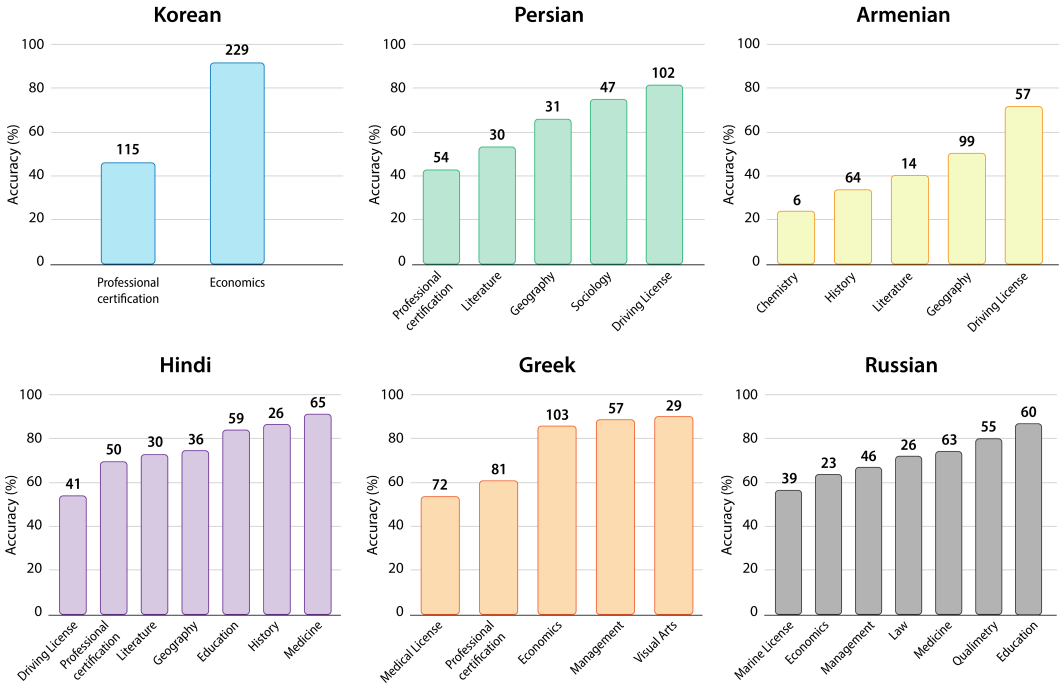


Figure 5: **GPT-4o performance across academic disciplines for Korean, Persian, Armenian, Hindi, Greek, and Russian**. Each bar is annotated with the number of questions with correct answers.

A APPENDIX

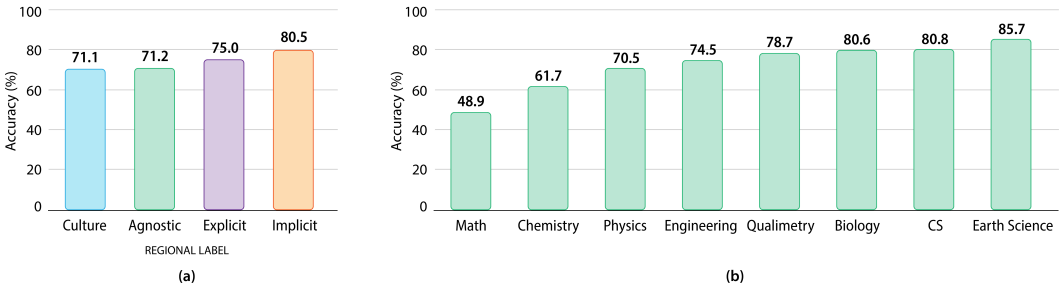


Figure 6: **GPT-4o model performance** on **INCLUDE-LITE**. (a) Performance across regional labels. While models typically perform better across *region-explicit* and *regional-implicit* questions, it is difficult to disentangle the difficult of questions due to regionality from the subject matter itself (*i.e.*, *region-agnostic* questions may contain more STEM subjects that are traditionally harder for LLMs). (b) Performance across academic disciplines within STEM area. We observe models perform particularly poorly on Math and Chemistry questions.

	Accuracy (↑)					
Model	**Humanities**	**STEM**	**Domain-Specific**	**Professional**	**Licenses**	**Average**
# samples	13294	2478	1940	3189	1736	-
GPT-4o						
- 5-shot	79.0	74.2	76.8	70.1	82.1	77.5
- Zero-shot CoT	79.9	78.6	80.4	73.8	81.1	79.0
C4AI-Aya-23-35b						
- 5-shot	54.8	52.3	48.1	56.9	48.8	51.8
- Zero-shot CoT	46.0	39.1	45.9	40.6	48.2	45.7
Aya-23-8B	34.0	34.3	33.2	40.6	29.9	32.5
Mistral-7B (v0.3)	44.2	43.4	43.9	38.6	44.3	43.3
Mistral-7B-Instruct (v0.3)	44.5	42.7	43.2	40.1	43.7	43.5
Gemma-7B	55.1	53.6	55.5	47.7	62.2	54.5
Gemma-7B-Instruct	38.6	37.7	42.0	34.5	44.9	38.7
Qwen2.5-7B	53.4	54.2	59.1	51.3	57.8	54.1
Qwen2.5-7B-Instruct	53.5	53.3	58.1	49.5	58.6	53.7
Qwen2.5-14B	**61.4**	**60.9**	**66.0**	**57.1**	**65.1**	**61.4**
Llama-3-8B	51.7	49.8	52.1	43.4	51.3	50.3
Llama-3-8B-Instruct	50.7	46.9	52.9	44.3	54.4	49.8
XGLM-7.5B	24.6	26.8	24.9	25.1	25.7	25.0
BLOOM-7.1B	25.1	27.2	26.0	25.1	24.0	25.3
BLOOMZ-7.1B	26.6	30.0	25.7	25.3	30.6	27.0

Table 2: Accuracy performance of GPT-4o on **INCLUDE-LITE** grouped by high-level topics. Where **Humanities** include Social Science, Humanities, and General knowledge. **STEM** includes Applied Science and STEM. **Domain-specific** covers Business & Commerce and Health oriented education. **Professional** includes professional certifications. **Licenses** cover Marine, Fishing, and Driving licenses.

Language	Academic Humanities	Academic STEM studies	Academic Domain-specific studies	Professional	License	Avg (%)
Albanian	95.0	88.0	83.5	-	-	89.50
Arabic	77.8	82.0	80.5	-	76.2	78.30
Armenian	52.7	32.0	-	-	72.2	53.60
Azerbaijani	71.3	73.6	71.4	-	-	71.90
Basque	-	-	-	64.8	-	64.80
Belarusian	51.8	42.0	-	-	-	50.90
Bengali	71.1	90.0	-	84.3	-	76.80
Bulgarian	93.8	60.0	-	-	-	90.70
Chinese	71.5	66.7	58.2	52.1	84.5	66.10
Croatian	89.0	82.0	-	-	-	88.40
Dutch; Flemish	86.6	87.5	80.0	-	-	86.40
Estonian	90.7	98.0	100.0	-	-	92.40
Finnish	67.0	87.0	77.8	-	-	69.90
French	83.8	50.0	81.2	-	68.1	80.70
Georgian	87.6	-	-	-	-	87.60
German	62.6	64.0	-	-	87.0	66.90
Greek	84.7	84.0	89.2	58.6	-	71.50
Hebrew	62.0	-	-	-	88.6	86.20
Hindi	77.7	71.9	91.5	71.8	57.7	75.10
Hungarian	66.3	80.6	-	-	-	75.80
Indonesian	84.0	69.1	-	84.8	-	79.50
Italian	87.7	87.2	91.7	95.5	-	90.00
Japanese	-	-	-	78.1	96.0	81.60
Kazakh	80.4	-	-	-	-	80.40
Korean	91.6	-	-	46.4	-	69.00
Lithuanian	92.0	97.1	82.5	81.2	-	90.60
Malay	84.5	-	80.3	-	-	83.00
Malayalam	69.6	66.0	55.0	-	80.9	70.80
Nepali	-	-	-	61.6	83.2	72.40
Macedonian	96.0	86.0	89.3	-	-	92.40
Persian	66.0	25.0	-	49.6	81.6	64.60
Polish	100.0	64.6	-	80.0	-	78.80
Portuguese	84.7	63.3	67.9	-	-	76.40
Serbian	92.2	86.0	-	-	-	91.60
Spanish	83.6	88.0	96.0	-	-	84.40
Tagalog	86.8	-	-	-	90.7	87.40
Tamil	70.6	54.0	-	-	-	69.10
Telugu	66.9	70.7	-	-	-	68.20
Turkish	62.0	52.0	75.9	-	-	65.30
Ukrainian	85.8	84.0	-	-	-	85.60
Urdu	61.7	65.3	100.0	-	-	62.50
Uzbek	63.6	84.0	-	73.3	-	69.70
Vietnamese	84.4	86.0	-	-	-	84.50
Russian	77.5	83.4	70.8	-	63.9	75.00

Table 3: Accuracy performance of GPT-4o (5-shot) on **INCLUDE-LITE** for each language. **Humanities** include Social Science, Humanities, and General knowledge. **STEM** includes Applied Science and STEM. **Domain-specific** covers Business & Commerce and Health oriented education. **Professional** includes professional certifications. **Licenses** cover Marine, Fishing, and Driving licenses.

A.1 COLLECTED LANGUAGES

Table 4 provides information about the languages in **INCLUDE**.

Language	Script	Family	Branch	Availability	Count
Albanian	latin	Indo-European	Albanian	Mid	2365
Amharic	ge'ez	Afro-Asiatic	Semitic	Low	131
Arabic	perso-arabic	Afro-Asiatic	Semitic	High	15137
Armenian	armenian	Indo-European	Armenian	Low	1669
Assamese	bengali-assamese	Indo-European	Indo-Iranian	Low	323
Azerbaijani	latin	Turkic	Azerbaijani North	Mid	6937
Basque	latin	Isolate		Low	719
Belarusian	cyrillic	Indo-European	Slavic East	Low	687
Bengali	bengali-assamese	Indo-European	Indo-Iranian	Mid	15259
Bulgarian	cyrillic	Indo-European	Slavic South Eastern	Mid	2937
Chinese	chinese	Sino-Tibetan	Chinese	High	12977
Croatian	latin	Indo-European	Slavic South Western	Mid	2879
Czech	latin	Indo-European	Slavic West	High	50
Danish	latin	Indo-European	Germanic	Mid	732
Dutch; Flemish	latin	Indo-European	Germanic	High	2222
Estonian	latin	Uralic	Finnic	Mid	952
Finnish	latin	Uralic	Finnic	Mid	1574
French	latin	Indo-European	Italic	High	2457
Georgian	mkherduli	Kartvelian	Georgian	Low	599
German	latin	Indo-European	Germanic	High	1590
Greek	greek	Indo-European	Greek	Mid	6570
Hebrew	hebrew	Afro-Asiatic	Semitic	Mid	2457
Hindi	devanagari	Indo-European	Indo-Iranian	Mid	5167
Hungarian	latin	Uralic	Hungarian	Mid	2267
Indonesian	latin	Austronesian	Malayo-Polynesian	High	12013
Italian	latin	Indo-European	Italic	High	3038
Japanese	kanji	Japonic	Japanese	High	2699
Kannada	kannada	Dravidian	Southern	Low	335
Kazakh	cyrillic	Turkic	Western	Low	5736
Korean	hangul	Koreanic	Korean	Mid	1781
Lithuanian	latin	Indo-European	Eastern Baltic	Mid	1397
Malay	latin	Austronesian	Malayo-Polynesian	Mid	1021
Malayalam	vatteluttu	Dravidian	Southern	Low	275
Marathi	devanagari	Indo-European	Indo-Iranian	Mid	313
Nepali	devanagari	Indo-European	Indo-Iranian	Mid	1470
Macedonian	cyrillic	Indo-European	Slavic South Eastern	Low	2075
Oriya	odia	Indo-European	Indo-Iranian	Low	241
Panjabi; Punjabi	gurmukhi	Indo-European	Indo-Iranian	Low	453
Persian	perso-arabic	Indo-European	Indo-Iranian	High	23990
Polish	latin	Indo-European	Slavic West	High	2023
Portuguese	latin	Indo-European	Italic	High	1407
Russian	cyrillic	Indo-European	Slavic East	High	10169
Serbian	cyrillic	Indo-European	Slavic South	Mid	1636
Sinhala; Sinhalese	sinhala	Indo-European	Indo-Iranian	Low	325
Slovak	latin	Indo-European	Slavic West	Mid	131
Spanish	latin	Indo-European	Italic	High	2559
Swedish	latin	Indo-European	Germanic	Mid	5102
Tagalog	latin	Austronesian	Malayo-Polynesian	Low	530
Tamil	tamil	Dravidian	Southern	Mid	945
Telugu	telugu	Dravidian	South-Central	Low	11568
Turkish	latin	Turkic	Southern	High	2710
Ukrainian	cyrillic	Indo-European	Slavic East	Mid	1482
Urdu	perso-arabic	Indo-European	Indo-Iranian	Low	122
Uzbek	latin	Turkic	Eastern	Low	2878
Vietnamese	latin	Austro-Asiatic	Mon-Khmer	High	8901

Table 4: Languages in **INCLUDE** with their associated metadata and the total count of the samples per language.

A.2 DETAILS ON EXAM SOURCES PARSING

Figure 9 presents the questionnaire we distributed to the community to gather a diverse set of multiple-choice exams. It was distributed among university student organizations and researchers at our institution.[6] Participation was voluntary and not incentivized.

A.3 PERFORMANCE ACROSS ACADEMIC AREAS AND FIELDS

Distribution of academic areas and academic fields with the respective number of questions is presented in Figure 7. GPT-4o performance across languages and academic areas is in Table 5. GPT-4o performance across languages, academic fields, and related regional features is in Tables 6 and 7.

A.4 REGIONAL LABELS: ANNOTATION

First, we categorized the exams into one of eight broad academic areas, *e.g.*, Humanities or Social Sciences, and then further classified each exam into a specific academic fields, *e.g.*, History or Geography. This categorization was done manually, taking into account both the exam's learning level and the exam's original topic.

Building on these categories, we applied one of four labels—agnostic, culture-related, region-explicit, or region-implicit—based on the degree of dependence on localized knowledge required to answer the exam questions. The labels reflect the extent to which specific cultural or regional knowledge is necessary. Table 8 provides examples illustrating how different exams were typically classified under each label, to show the relationship between categories and labels.

The "region implicit" label was applied when we suspected that exam content might vary across regions but could not reliably detect specific regional differences. For example, historical events, literary works, and religious interpretations may differ significantly depending on the region. Similarly, fields like marketing, management, social work, and insurance—though rooted in shared theoretical foundations—can be practiced differently across regions. When we encountered such uncertainty, we labeled the subject as "region implicit."

Within the Humanities, fields such as Visual Arts, History, Philosophy, Religious Studies, Performing Arts, Culturology, and Literature were labeled "region implicit" when the content was not explicitly tied to a particular region. However, if the exam was region-specific (*e.g.*, Greek literature), we categorized it as "culture-related."

In the Social Sciences, Psychology was classified as "region explicit" if the exam focused on regional clinical practices; otherwise, it was "region implicit" when dealing with broader psychological theories that may vary across regions. Geography was labeled "region implicit" if the exam involved political geography and "agnostic" if it focused on general geographic knowledge. Similarly, disciplines like Sociology, Political Science, and Anthropology were classified as either "region implicit" or "culture-related," depending on whether regional specificity was required, much like History.

For Economics, exams were labeled "agnostic" when covering general economic theories, "region explicit" when addressing regional regulations, and "region implicit" when regional applications were uncertain. In STEM fields, most disciplines were categorized as "agnostic," with the exception of Qualimetry, which was labeled "region explicit" due to its specific application in post-Soviet countries for quantitative and qualitative assessment according to regional standards.[7]

Exams related to theoretical medical subjects, such as Anatomy, were classified as "agnostic." In contrast, exams covering clinical practices and guidelines specific to a region were labeled as "region explicit," while others were marked as "region implicit" if regional dependence was unclear.

Accounting is generally tied to region-specific practices, so it was consistently classified as "region explicit." Other disciplines within the Business and Commerce category were treated similarly to Economics and labeled as mostly as "region implicit." In some cases, there were "agnostic" and "region explicit" exams.

[6] We will provide institutional details upon paper publication.

[7] https://en.wikipedia.org/wiki/Qualimetry

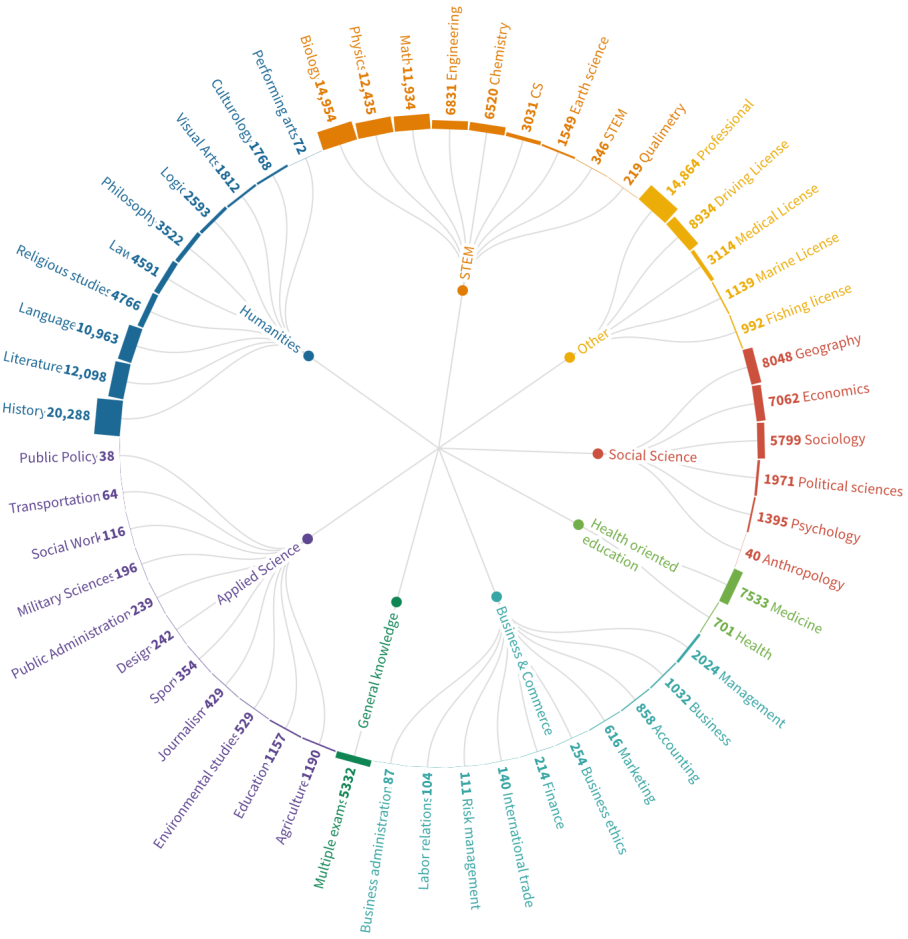


Figure 7: **Academic domain and academic fields with the number of examples across all languages.**

Exams in Applied Science disciplines were typically categorized as "region implicit" due to the potential involvement of regional variations. Similarly, exams in Military Sciences, Public Administration, and Public Policy were marked as "region explicit" when tied to specific regions (*e.g.*, Basics of National Security of the Republic of Azerbaijan) and "region implicit" when regional specifics were less pronounced. For exams focused on theoretical aspects, we used the "agnostic" label (*e.g.*, Theoretical Foundations of Food Engineering in Agriculture).

Finally, exams covering multiple topics were classified as "region implicit" unless they explicitly focused on cultural aspects of a particular region, in which case they were labeled as "culture-related."

A.5 Implementation Details

Each model was evaluated using a single A100 GPU (80GB memory), with evaluation times averaging approximately 4 hours for **Include-lite**. For all models, we set the decoding temperature to 0, prioritizing deterministic outputs.

We configured response context windows based on model size and task requirements. For models such as Aya-23-8B, Mistral-7B (v0.3), Mistral-7B-Instruct (v0.3), Gemma-7B, Gemma-7B-Instruct, Qwen2.5-7B, Qwen2.5-7B-Instruct, Llama-3-8B, Llama-3-8B-Instruct, XGLM-7.5B, BLOOM-7.1B,

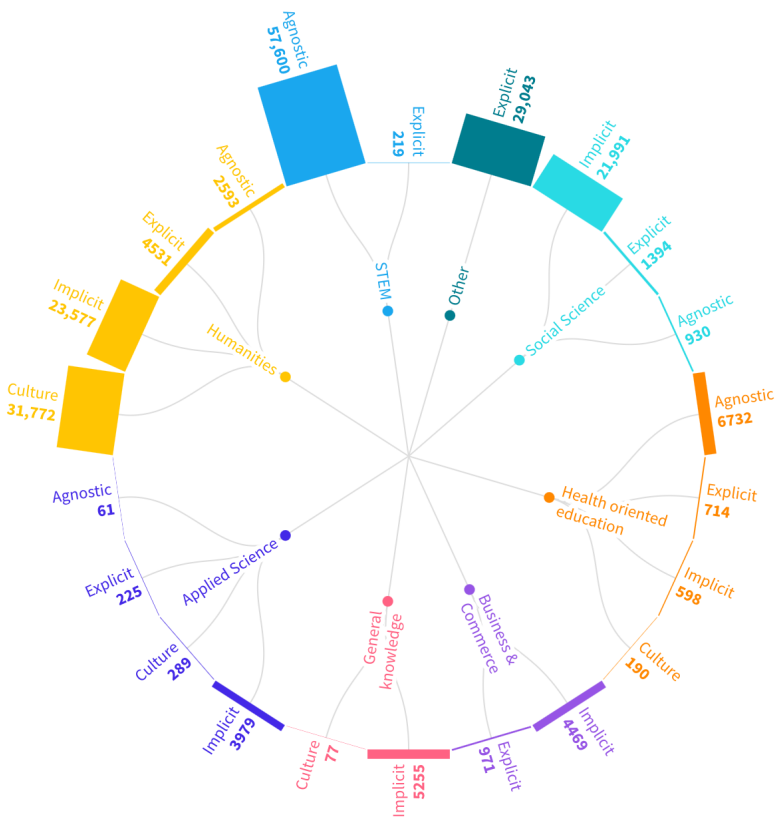


Figure 8: **Distribution of regional labels per Academic area.**

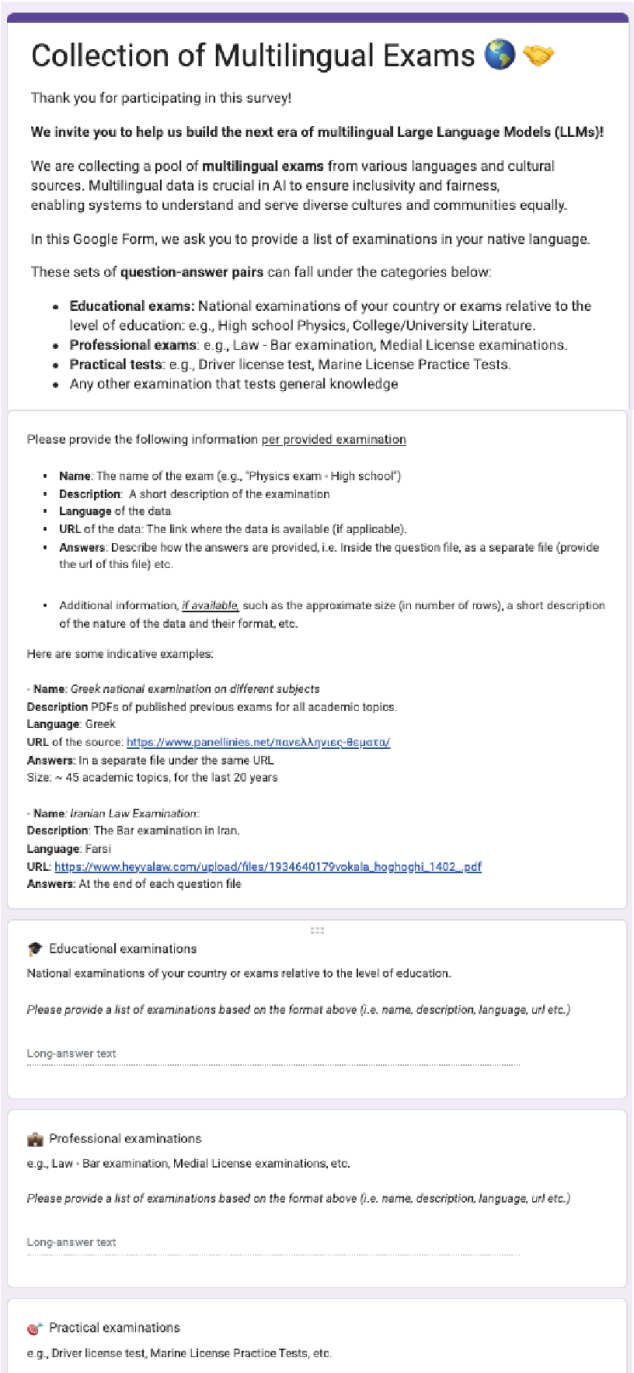
and BLOOMZ-7.1B, we set a window size of 40 tokens. Larger models, including C4AI-Aya-23-35B and GPT-4, were evaluated using a 512-token context window for 5-shot tasks and 1024 tokens for zero-shot chain-of-thought (CoT) reasoning.

A.6 Experiments with English prompts

We conducted new experiments where the user prompt instructions were translated into English while keeping the text of the question and the choices in the native language. We present new results for the most performant model variants within each model family, evaluated using both English and native language prompts in Table 10. These new results suggest that English prompts can provide modest benefits for most models (with aya-expanse-8b and 32b achieving more significant increases), but that performance is generally within 1-2% of the performance of native language prompts.

A.7 Experiments on monolingual models

To assess the performance of monolingual models on our benchmark, we evaluate seven open-source monolingual models on the relevant language-specific subsets of INCLUDE, (i.e., the languages these models were pre-trained on). We compare their performance with the results of the most performant large-, medium-, and small-scale models on the specific language subsets. The results



Collection of Multilingual Exams 🌍🤝

Thank you for participating in this survey!

We invite you to help us build the next era of multilingual Large Language Models (LLMs)!

We are collecting a pool of **multilingual exams** from various languages and cultural sources. Multilingual data is crucial in AI to ensure inclusivity and fairness, enabling systems to understand and serve diverse cultures and communities equally.

In this Google Form, we ask you to provide a list of examinations in your native language.

These sets of **question-answer pairs** can fall under the categories below:

- **Educational exams:** National examinations of your country or exams relative to the level of education: e.g., High school Physics, College/University Literature.
- **Professional exams**: e.g., Law - Bar examination, Medial License examinations.
- **Practical tests**: e.g., Driver license test, Marine License Practice Tests.
- Any other examination that tests general knowledge

Please provide the following information per provided examination

- **Name**: The name of the exam (e.g., "Physics exam - High school")
- **Description**: A short description of the examination
- **Language** of the data
- **URL** of the data: The link where the data is available (if applicable).
- **Answers**: Describe how the answers are provided, i.e. Inside the question file, as a separate file (provide the url of this file) etc.

- Additional information, *if available*, such as the approximate size (in number of rows), a short description of the nature of the data and their format, etc.

Here are some indicative examples:

- **Name**: *Greek national examination on different subjects*
Description PDFs of published previous exams for all academic topics.
Language: Greek
URL of the source: https://www.panellinies.net/πανελλήνιες-θέματα/
Answers: In a separate file under the same URL
Size: ~ 45 academic topics, for the last 20 years

- **Name**: *Iranian Law Examination*:
Description: The Bar examination in Iran.
Language: Farsi
URL: https://www.heyvalaw.com/upload/files/1934640179vokala_hoghoghi_1402_.pdf
Answers: At the end of each question file

🎓 Educational examinations

National examinations of your country or exams relative to the level of education.

Please provide a list of examinations based on the format above (i.e. name, description, language, url etc.)

Long-answer text

🏢 Professional examinations

e.g., Law - Bar examination, Medial License examinations, etc.

Please provide a list of examinations based on the format above (i.e. name, description, language, url etc.)

Long-answer text

🎯 Practical examinations

e.g., Driver license test, Marine License Practice Tests, etc.

Figure 9: Exam source collection form sent to the academic community.

of this evaluation are presented in the Table 11. The table reveals that most monolingual models underperform the state-of-the-art small multilingual model Qwen-2.5 (7B), with the exception of the German monolingual model, SauerkrautLM-v2-14B-DPO, which performs on par with Qwen in the German language.

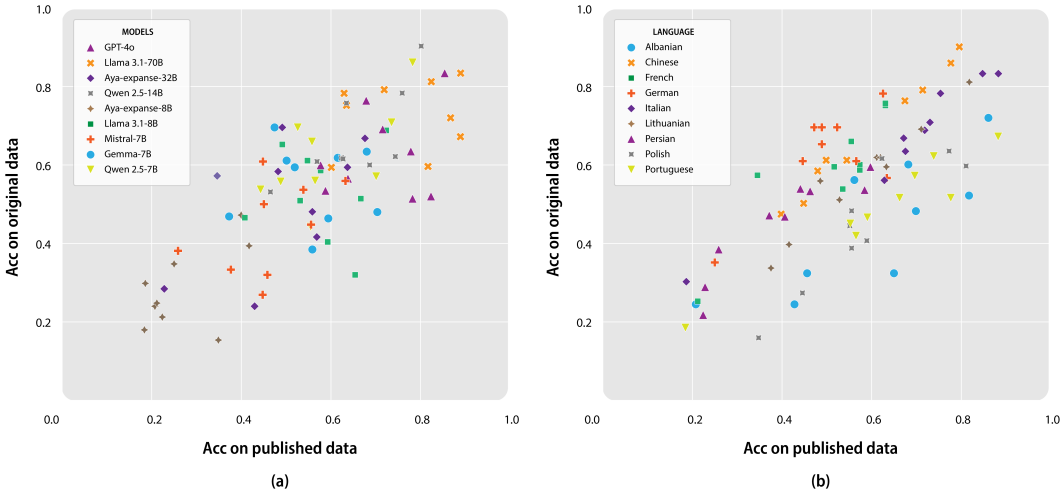


Figure 10: Accuracy of different models on languages where both existing benchmark data and newly collected data are available. Each point represents the accuracy score of a model for a specific language. (a) Points of the same color represent the accuracy scores of a single model across different languages. (b) Points of the same color represent the accuracy scores for a single language across different models.

A.8 Experiments with regional prompts

We conduct experiments that include the region and the language of each sample in the prompt instructions, asking the model to consider the cultural and linguistic nuances specific to that region. We present results in Table 12 for the best-performing large, medium, and small-scale models on specific language subsets across these two settings. We further stratify the results based on the type of knowledge: region agnostic or region related. The results confirm our hypothesis that providing explicit region and language information does not enhance model performance in this setting. We encourage future INCLUDE users to experiment with different configurations and prompting strategies to further explore the extent of model performance.

A.9 Limitations of the scope of existing benchmarks

As discussed in the motivation and related work sections, there is currently no multilingual benchmark that offers both high language coverage and incorporates regional knowledge. Existing benchmarks typically fall into one of two categories: either they focus extensively on a single language across various regional dimensions, or they cover a certain number of languages with predominantly agnostic knowledge. In Table 14, we provide more details on the list of existing benchmarks that were mentioned in the paper, which feature original content (not machine-translated), highlighting their language and knowledge coverage.

In relation to these monolingual existing resources, the **INCLUDE** benchmark makes three significant contributions: (1) introduces original datasets from languages that are either not covered or only partially covered by existing benchmarks, (2) leverages publicly available, knowledge-intensive multiple-choice question benchmarks in various languages, (3) organizes both the existing and newly introduced data under a unified taxonomy of knowledge, differentiating between regional knowledge and region-agnostic knowledge. In this context, **INCLUDE** incorporates existing datasets, which account for 39.8% of the total collected data and 31.7% of the **INCLUDE-LITE** benchmark. To understand the correlations between the newly collected data and the existing benchmarks integrated into **INCLUDE**, we analyzed model performance in languages where both existing benchmark data and newly collected data are available. We compared performance across these datasets and examined the correlation between them. Results were stratified by language and by model type. We visualized the performances using plots (Figure 10) and calculated the R^2 scores to quantify the correlations (Table 13).

The analysis reveals two key conclusions: First, for a given language with multiple models having published performance data, a model's performance on **INCLUDE** can generally be predicted. However, for a given model with published performance across different languages, its performance on **INCLUDE** cannot reliably be predicted when applied to a newly published language benchmark. This indicates that while **INCLUDE** is less impactful for languages with existing published benchmarks, it is particularly valuable for assessing performance in languages with no prior resources.

A.10 ANALYSIS OF OUTPUT ERRORS ON INCLUDE

As outlined in Section 5.3 of the paper, model performance—and consequently, the errors—are heavily influenced by the model's proficiency in the specific task and language. We conducted a more detailed error analysis by manually investigating a sample of **INCLUDE** generations. We focused on six languages spanning high-resource (Chinese, Turkish), medium-resource (Bengali, Greek, Korean), and low-resource (Armenian) categories, selecting subject areas with the largest performance gaps compared to other subjects within the same language. We manually examined 150 examples, covering at least two subjects per language with 10 examples per subject, analyzing the questions and answers generated by GPT-4o. We observed four main types of errors related to computational mistakes, factual mistakes, lack of regional knowledge, and model hallucinations (Table 15). Each error type highlights distinct limitations in the model's capabilities, from arithmetic and factual knowledge to regional understanding and prompt adherence. Our analysis revealed that the model's errors were distributed as follows: 38.6% were due to a lack of regional knowledge, 32% resulted from hallucinations, 26.7% were factual mistakes, and 2.7% were computational errors.

A.11 DATA CONTAMINATION PREVENTION

As described in Section 3.1, **INCLUDE** is made up of a few previously-published benchmarks incorporated into **INCLUDE**, but also newly-collected exam materials from sources contributed by our multilingual community of native speakers. A significant portion of the newly-collected data was derived from PDFs and textbooks, which are less likely to have been included in models trained primarily on web-based data.

In this section, we analyze the degree of contamination within the models using the mink%++ (Zhang et al., 2024b) method for training data detection in LLMs. This method determines whether an input next token forms a mode or has a relatively high probability under the conditional categorical distribution. Using this scoring mechanism, one can predict if an input sequence is part of the model's training data based on a decision threshold. This method achieves SOTA on the WikiMIA (Shi et al., 2023) benchmark for training data detection. We use the decision threshold that achieves the best performance on WikiMIA as the decision threshold for our analysis. Using this method, we computed the contamination rate for each language on four main-stream multilingual models: Aya-8B, XGLM-7B, LLaMA-3.1-8B, and Qwen-2.5-7B. We show the contamination rate results in Table 16.

To further mitigate the risk of benchmark saturation as a result of data leakage when new models are trained, we have held back the complete dataset, comprising 197,243 entries. Instead, we will release these further questions and answers incrementally over the next year. We have also reserved a held-out dataset covering a wide range of the collected languages to be used for future experimental studies specifically aimed at analyzing data leakage over time.

Language	Academic Area	Accuracy	Count
Albanian	Humanities	95.1	223
	Business & Commerce	85.7	223
	Social Science	94.5	55
Arabic	Humanities	79.0	105
	Business & Commerce	79.3	82
	General Knowledge	86.7	105
	Other	76.2	105
	STEM	82.0	50
	Social Science	67.6	105
Armenian	Humanities	34.7	225
	Other	72.2	79
	STEM	28.0	50
	Social Science	50.5	196
Azerbaijani	Applied Science	75.9	108
	Humanities	74.1	108
	Business & Commerce	62.5	96
	Health-Oriented Education	80.2	96
	Social Science	67.6	108
Basque	Other	64.8	500
Belarusian	Humanities	50.8	490
	STEM	42.0	50
Bengali	Humanities	62.0	166
	General Knowledge	80.1	166
	Other	84.3	166
	STEM	88.0	50
Bulgarian	Humanities	96.4	250
	STEM	60.0	50
	Social Science	91.2	250
Chinese	Applied Science	73.2	71
	Humanities	67.8	87
	Business & Commerce	53.5	71
	Health-Oriented Education	60.9	87
	Other	68.3	142
	Social Science	76.1	71
Croatian	Humanities	86.8	250
	STEM	82.0	50
	Social Science	90.8	250
Dutch; Flemish	Humanities	86.0	243
	Social Science	86.8	243
Estonian	Humanities	90.1	161
	STEM	97.2	36
Finnish	Humanities	69.5	226
	Health-Oriented Education	75.6	45
	Social Science	64.6	226
French	Humanities	86.5	266
	Other	68.1	47
	Social Science	74.3	74
Georgian	Humanities	87.6	500
German	Social Science	62.6	91
Greek	Humanities	83.8	37
	Business & Commerce	89.1	64
	Other	57.5	266
	Social Science	84.2	133
Hebrew	Humanities	60.0	50
	Other	88.6	500
Hindi	Applied Science	83.1	71
	Humanities	72.9	96
	General Knowledge	83.1	71
	Health-Oriented Education	91.5	71
	Other	64.1	142
	Social Science	74.6	71
Hungarian	Applied Science	79.8	341
	Social Science	66.3	184
Indonesian	Applied Science	71.2	125
	Humanities	82.4	125
	Other	83.2	125
	STEM	60.0	50
	Social Science	84.8	125
Italian	Applied Science	85.7	35
	Humanities	85.0	167
	Other	95.5	155
	Social Science	89.8	167

Language	Academic Area	Accuracy	Count
Japanese	Other	80.2	501
Kazakh	Humanities	80.4	500
Korean	Other	46.0	250
	Social Science	91.6	250
Lithuanian	Humanities	91.6	335
	Business & Commerce	77.5	40
	Other	81.2	48
	STEM	97.1	34
	Social Science	93.5	77
Malay	Humanities	84.3	178
	Business & Commerce	79.8	178
	Social Science	84.8	145
Malayalam	Humanities	64.3	56
	General Knowledge	73.1	78
	Health-Oriented Education	55.0	100
	Other	80.9	194
	STEM	66.0	47
Nepali	Other	72.4	500
Macedonian	Humanities	96.9	224
	Business & Commerce	89.3	224
	STEM	86.0	50
	Social Science	92.5	53
Persian	Humanities	55.3	141
	Other	62.4	250
	Social Science	74.5	141
Polish	Other	80.0	496
	STEM	62.5	48
Portuguese	Applied Science	58.3	84
	Humanities	81.8	154
	Business & Commerce	56.9	84
	Health-Oriented Education	67.1	67
	Other	67.6	169
Russian	Applied Science	87.0	69
	Humanities	76.8	69
	Business & Commerce	66.7	69
	Health oriented education	74.1	85
	Other	63.9	97
	STEM	80.9	94
	Social Science	76.8	69
Serbian	Humanities	90.4	313
	STEM	84.0	50
	Social Science	95.2	187
Spanish	Humanities	77.2	250
	Health oriented education	96.0	25
	STEM	88.0	25
	Social Science	89.6	250
Tagalog	Humanities	86.8	425
	Other	90.7	75
Tamil	General knowledge	70.6	500
	STEM	54.0	50
Telugu	Applied Science	73.5	166
	Humanities	66.0	191
	Social Science	66.9	166
Turkish	Humanities	62.0	166
	Business & Commerce	75.9	166
	STEM	52.0	50
	Social Science	62.0	166
Ukrainian	Humanities	92.4	250
	STEM	84.0	50
	Social Science	79.2	250
Urdu	Humanities	61.7	300
	STEM	63.3	49
Uzbek	Humanities	62.9	240
	Other	73.3	240
	STEM	84.0	50
	Social Science	71.4	21
Vietnamese	Humanities	88.0	250
	STEM	86.0	50
	Social Science	80.8	250

Table 5: GPT-4o (5-shot) performance on **INCLUDE-LITE** per language and academic area. Areas with less than 30 examples were excluded from the analysis.

Language	Academic Field	Regional Feature	Accuracy	Count
Albanian	History	Implicit	93.1	58
	Philosophy	Implicit	97.6	82
	Visual Arts	Implicit	94.0	83
	Business	Implicit	85.7	223
	Sociology	Implicit	94.5	55
Arabic	History	Implicit	73.3	30
	Language	Culture	80.0	40
	Accounting	Explicit	89.5	57
	Multiple exams	Implicit	86.7	105
	Driving License	Explicit	76.2	105
	Geography	Implicit	65.3	49
	Sociology	Implicit	66.7	33
Armenian	History	Culture	26.3	95
	History	Implicit	41.1	95
	Literature	Culture	40.0	35
	Driving License	Explicit	72.2	79
	Chemistry	Agnostic	20.0	30
	Geography	Implicit	50.5	196
Azerbaijani	Agriculture	Implicit	85.3	34
	Law	Explicit	76.2	42
	Management	Implicit	66.7	36
	Health	Implicit	80.2	96
	Economics	Implicit	70.7	58
Basque	Professional certification	Explicit	64.8	500
Belarusian	Language	Culture	47.9	426
	Literature	Culture	67.4	43
	Math	Agnostic	40.8	49
Bengali	Language	Culture	62.5	40
	Literature	Culture	61.9	126
	Multiple exams	Implicit	80.1	166
	Professional certification	Explicit	84.3	166
	Biology	Agnostic	89.5	38
Bulgarian	History	Implicit	93.9	115
	Philosophy	Implicit	98.5	135
	Geography	Implicit	91.2	250
Chinese	Medicine	Explicit	57.1	35
	Driving License	Explicit	84.5	71
	Professional certification	Explicit	52.1	71
	Political sciences	Implicit	84.8	33
Croatian	History	Implicit	88.2	119
	Philosophy	Implicit	83.5	79
	Religious Studies	Implicit	90.2	51
	Psychology	Implicit	95.7	93
	Sociology	Implicit	94.8	135
Dutch; Flemish	History	Culture	89.4	141
	Literature	Culture	81.4	102
	Economics	Implicit	81.7	109
	Geography	Implicit	93.9	33
	Sociology	Implicit	90.1	101
Estonian	Language	Culture	89.1	147
Finnish	Law	Explicit	69.3	215
	Economics	Implicit	73.7	95
	Political Sciences	Implicit	61.5	96
	Sociology	Implicit	48.6	35
French	Culturology	Culture	94.8	77
	Language	Culture	79.0	124
	Driving License	Explicit	68.1	47
	Geography	Implicit	68.1	47
Georgian	History	Implicit	93.8	161
	Language	Culture	85.7	168
	Law	Explicit	83.6	171
German	Geography	Implicit	50.0	54
Greek	Visual Arts	Implicit	90.6	32
	Management	Implicit	89.1	64
	Medical License	Explicit	54.1	133
	Professional Certification	Explicit	60.9	133
	Economics	Implicit	85.8	120
Hebrew	Logic	Agnostic	60.0	50
	Driving License	Explicit	88.6	500
Hindi	Education	Implicit	84.3	70
	History	Implicit	86.7	30
	Literature	Culture	73.2	41
	Multiple Exams	Implicit	83.1	71
	Medicine	Explicit	91.5	71
	Driving License	Explicit	57.7	71
	Professional Certification	Explicit	70.4	71
	Geography	Implicit	75.0	48

Table 6: GPT-4o (5-shot) performance on **INCLUDE-LITE** per language, academic field, and regional label. Fields with less than 30 examples were excluded from the analysis (Part 1)

Language	Academic Field	Regional Feature	Accuracy	Count
Hungarian	Agriculture	Implicit	82.4	170
	Architecture and Design	Explicit	85.7	42
	Environmental Studies and Forestry	Implicit	74.4	129
	Economics	Implicit	80.8	78
	Geography	Implicit	48.1	81
Indonesian	Human Physical Performance and Recreation	Implicit	71.2	125
	Language	Culture	79.5	78
	Professional Certification	Region explicit	83.2	125
	Economics	Region explicit	77.8	36
	Geography	Implicit	87.5	32
	Sociology	Implicit	87.7	57
Italian	Agriculture	Implicit	85.7	35
	History	Implicit	90.4	94
	Professional Certification	Region explicit	95.5	155
	Psychology	Implicit	95.0	60
	Sociology	Implicit	87.7	65
Japanese	Driving License	Region explicit	96.0	99
	Medical License	Region explicit	86.1	201
	Professional Certification	Region explicit	66.7	201
Kazakh	History	Culture	78.4	241
	History	Implicit	94.9	79
	Literature	Culture	76.7	180
Korean	Professional Certification	Region explicit	46.0	250
	Economics	Implicit	91.6	250
Lithuanian	History	Implicit	91.6	335
	Finance	Implicit	77.5	40
	Professional Certification	Region explicit	81.2	48
	Earth Science	Agnostic	97.1	34
	Economics	Implicit	93.5	77
Malay	History	Implicit	84.3	178
	Accounting	Region explicit	79.8	178
	Geography	Implicit	85.3	129
Malayalam	History	Implicit	61.5	52
	Multiple Exams	Culture	72.7	77
	Health	Implicit	55.0	100
	Marine License	Explicit	80.9	194
Nepali	Driving License	Explicit	83.2	250
	Professional Certification	Explicit	61.6	250
North Macedonian	History	Implicit	95.8	48
	Philosophy	Implicit	97.3	74
	Visual Arts	Implicit	97.1	102
	Business	Implicit	89.3	224
	Sociology	Implicit	92.5	53
Persian	Literature	Culture	51.6	31
	Driving License	Explicit	81.6	125
	Professional Certification	Explicit	43.2	125
	Geography	Implicit	66.0	47
	Sociology	Implicit	74.6	63
Polish	Professional Certification	Explicit	80.0	496
	Math	Agnostic	61.7	47
Portuguese	Agriculture	Implicit	70.0	40
	Philosophy	Implicit	83.3	84
	Management	Implicit	57.9	57
	Health	Implicit	70.3	37
	Economics	Implicit	89.7	126
Russian	Education	Implicit	87.0	69
	Law	Explicit	72.2	36
	Management	Implicit	66.2	65
	Medicine	Explicit	73.3	60
	Marine License	Explicit	56.5	69
	Qualimetry	Explicit	79.7	69
	Economics	Implicit	63.9	36
Serbian	History	Implicit	91.5	235
	Philosophy	Implicit	87.5	56
	Psychology	Implicit	99.2	125
	Sociology	Implicit	91.1	45
Spanish	Language	Culture	69.6	46
	Law	Explicit	67.0	109
	Literature	Implicit	93.8	64
	Philosophy	Implicit	90.3	31
	Economics	Explicit	95.6	91
	Geography	Implicit	86.2	159
Tagalog	Culturology	Culture	91.6	203
	History	Culture	85.3	116
	Language	Culture	79.2	106
	Driving License	Explicit	90.7	75
Tamil	Multiple Exams	Implicit	70.6	500
Telugu	Education	Implicit	73.0	100
	History	Culture	64.7	119
	History	Implicit	63.9	36
	Economics	Explicit	60.0	45
	Geography	Implicit	73.2	82
	Political Sciences	Implicit	63.3	30
Turkish	History	Implicit	71.2	73
	Philosophy	Implicit	74.6	63
	Business	Implicit	75.9	166
	Geography	Implicit	53.8	130
	Sociology	Implicit	91.7	36
Ukrainian	Law	Explicit	92.4	250
	Physics	Agnostic	84.0	50
	Psychology	Implicit	79.2	250
Urdu	Culturology	Culture	61.7	300
Uzbek	History	Implicit	66.1	124
	Law	Explicit	60.6	109
	Medical License	Explicit	73.3	240
Vietnamese	History	Implicit	88.3	239
	Geography	Implicit	80.8	250

Table 7: GPT-4o (5-shot) performance on **INCLUDE-LITE** per language, academic field, and regional label. Fields with less than 30 examples were excluded from the analysis (Part 2)

Academic area	Academic field	Label
Humanities	Logic	Agnostic
	Law	Region Explicit
	Language	Culture
	Visual Arts, History, Philosophy, Religious studies, Performing arts, Culturology, Literature	Region implicit/ Culture
Social Science	Sociology, Political sciences, Anthropology	Region implicit/Culture
	Economics	Region implicit/Agnostic/Region explicit
	Psychology	Region implicit/Region explicit
	Geography	Region implicit/Agnostic
STEM	Math, Physics, CS, Biology, Earth science, Chemistry, Engineering	Agnostic
	Qualimetry	Region explicit
Health oriented education	Medicine	Agnostic/Region implicit/Region explicit
	Health	Region implicit/Region explicit
Business and Commerce	Accounting	Region explicit
	Management, Marketing, Industrial and labor relations, International trade, Risk management and insurance, Business administration, Business ethics, Business, Finance	Region implicit/Region explicit/Agnostic
Applied Science	Agriculture, Library and museum studies, Transportation	Region implicit/Agnostic
	Military Sciences, Public Administration, Public Policy	Region implicit/Region explicit
	Architecture and Design, Family and consumer science, Environmental studies and forestry, Education Journalism, media studies, and communication, Social Work, Human physical performance and recreation	Region implicit
Other	Driving license, Marine license, Fishing license, Medical license, Public administration, Professional certification	Region explicit
General knowledge	Multiple exams	Region implicit/Culture

Table 8: Annotation schema for high-level **Academic area** and fine-grained **Academic field**. The **Label** column lists the most likely *regionality* label for these exams in our dataset (*e.g.*, *region-*{*agnostic, implicit, explicit*} or *cultural*), though all exams from which we collect data are individually labeled with a *regionality* category. The first label is the most frequent one.

Language	Acc (k:50)	Acc (k:100)	Acc (k:200)	Acc (k:512)	Total gain
Uzbek	51.4	60.6	66.6	68.6	17.2
Armenian	28.0	30.7	36.0	41.1	13.1
Malayalam	57.0	57.4	61.0	69.9	12.9
Urdu	53.7	56.8	58.8	62.2	8.5
Greek	58.0	58.2	63.8	66.4	8.4
Korean	60.4	61.0	62.4	68.8	8.4
Chinese	57.2	61.8	63.5	65.5	8.3
Finnish	63.3	64.4	67.0	69.1	5.8
Basque	60.0	60.8	63.8	64.8	4.8
Polish	74.1	75.2	75.4	78.1	4.0
Azerbaijani	67.7	69.2	70.4	71.5	3.8
Dutch; Flemish	81.9	82.9	83.8	85.3	3.4
Telugu	63.9	63.9	64.8	66.6	2.7
Hindi	72.0	72.4	73.7	74.4	2.4
German	64.0	65.5	65.5	66.2	2.2
Malay	80.6	81.8	82.4	82.8	2.2
Tamil	67.3	67.3	67.8	69.5	2.2
Arabic	76.3	76.8	77.9	78.4	2.1
russian	72.6	73.6	74.1	74.6	2.0
Italian	88.0	88.5	89.2	89.6	1.6
Spanish	82.4	83.1	83.3	84.0	1.6
Japanese	78.6	78.6	79.4	80.0	1.4
Georgian	86.2	86.4	87.0	87.6	1.4
Vietnamese	82.4	82.5	84.9	83.8	1.4
Turkish	63.5	64.1	64.4	64.8	1.3
Kazakh	79.2	79.6	80.4	80.4	1.2
Portuguese	72.8	73.5	73.5	74.0	1.2
Bengali	75.2	75.4	76.1	76.3	1.1
Persian	60.9	61.1	61.3	61.9	1.0
Belarusian	49.5	50.0	50.0	50.2	0.7
French	80.0	80.2	80.4	80.7	0.7
Indonesian	77.8	78.2	78.4	78.5	0.7
Albanian	88.9	89.3	89.3	89.5	0.6
Lithuanian	89.7	89.7	90.1	90.3	0.6
Estonian	92.0	92.0	92.4	92.4	0.4
Croatian	87.8	88.0	88.2	88.0	0.2
Hungarian	75.3	75.3	75.5	75.5	0.2
Nepali	71.8	72.0	71.6	72.0	0.2
Bulgarian	90.7	90.7	90.7	90.7	0.0
Hebrew	86.0	86.0	86.0	86.0	0.0
Macedonian	92.4	92.4	92.4	92.4	0.0
Serbian	91.5	91.5	91.5	91.5	0.0
Tagalog	87.4	87.4	87.4	87.4	0.0
Ukrainian	85.5	85.5	85.5	85.5	0.0

Table 9: **GPT-4o performance for different values of** k (the output generation length) per language on **INCLUDE-LITE** and total performance gain from k = 50 to 512.

Model	Native Language Prompt	English Prompt
GPT-4o	76.9	76.3
Aya-expanse-32B	52.4	56.0
Llama3.1-70B-Instruct	70.6	70.7
Aya-expanse-8B	37.1	46.0
Mistral-7B	44.1	44.9
Gemma-7B	54.5	54.9
Qwen2.5-7B	54.1	55.2
Qwen2.5-14B	61.4	61.7
Llama-3.1-8B	51.0	51.8

Table 10: Accuracy of the model for answering **INCLUDE-LITE** questions with user prompt instructions in the native language of each sample and with user prompt instructions in English.

Major training language	SoTA Monolingual	Monolingual Acc	GPT-4o	Qwen2.5-14B	Qwen2.5-7B
Chinese	**Baichuan-7B**	38.7	68.1	82.2	78.3
Arabic	**SILMA-9B-Instruct**	56.9	78.1	70.5	61.6
Japanese	**calm2-7b-chat**	25.0	75.0	69.2	64.7
Korean	**Korean-Mistral-Nemo-sft-dpo-12B**	35.3	75.0	83.2	76.8
Russian	**ruGPT-3.5-13B**	53.8	69.0	68.2	59.6
German	**SauerkrautLM-v2-14b-DPO**	56.8	66.2	58.3	56.1

Table 11: Accuracy of the multilingual and monolingual models for answering **INCLUDE-LITE** questions for specific target languages.

	Original Prompt			Regional Prompt		
Model	**Overall Acc**	**Region Agnostic**	**Region Related**	**Overall Acc**	**Region Agnostic**	**Region Related**
GPT-4o	76.9	71.2	77.5	76.2	69.9	76.7
Aya-expanse-32B	52.4	52.1	52.7	49.7	43.2	50.4
Qwen2.5-14B	61.4	61.2	61.7	61.1	60.9	61.1
Llama-3.1-8B	51.0	47.6	53.9	51.0	46.4	51.4
Qwen2.5-7B	54.1	54.7	54.0	54.0	54.4	53.9

Table 12: Accuracy of the models for answering **INCLUDE-LITE** questions for two prompting settings stratified by the regional feature.

Language	R^2	**Model**	R^2
Albanian	0.646	**GPT-4o**	0.077
Chinese	0.985	**Qwen2.5-14B**	0.546
French	0.770	**Aya-expanse-32B**	0.290
German	0.495	**Aya-expanse-8B**	0.333
Italian	0.953	**Qwen2.5-7B**	0.412
Lithuanian	0.945	**Mistral-7B**	0.231
Persian	0.833	**Gemma-7B**	0.001
Polish	0.831	**Llama 3.1-70B**	0.020
Portuguese	0.930	**Llama 3.1-8B**	0.001

Table 13: R^2 scores between the performance different models for newly-collected data and existing benchmarks stratified by language and model.

Benchmark	**Language coverage**	**Knowledge Coverage**	**Region agnostic (%)**	**Region related (%)**
ArabicMMLU [1]	Arabic	Academic knowledge (elementary school, high school, university), Driving License	24.8%	75.2%
CMMLU [2]	Chinese	Academic knowledge (elementary school, high school, university)	25.6%	74.4%
PersianMMLU [3]	Persian	Academic knowledge (elementary school, high school, university)	63.1%	36.9%
TurkishMMLU [4]	Turkish	Academic knowledge (elementary school, high school, university)	34.8%	65.2%
VNHSGE [6]	Vietnamese	High school examinations	40.4%	59.6%
EXAMS [7]	16 languages	High school examinations	43.7%	56.3%
INCLUDE (ours)	**44 languages**	**Academic knowledge (elementary school, high school, university), Professional examinations (Medical exam, Bar exam, Teaching exam), Occupational Licenses (Driving license, Marine license and more)**	7.8%	**92.2%**

Table 14: Existing published benchmarks descriptives and the comparison with **INCLUDE-LITE**.

Error type	Description	Percentage of errors (%)
Computational Errors	Errors that occur when the model fails to perform arithmetic required to answer a question correctly.	2.7%
Factual Knowledge Errors	Errors that involve the model lacking knowledge of facts unrelated to a specific region or language. For example, in the question, "Which of the following has a value between 1 and 1000? Choices: [Gini coefficient, base interest rate, personal credit score, corporate economic survey index]," the model may choose incorrectly due to a lack of factual knowledge.	26.7%
Regional Knowledge Errors	Errors that arise when the model lacks knowledge specific to a particular region, even though it demonstrates proficiency in the language itself.	38.6%
Model Hallucinations	Errors that occur when the model fails to follow the prompt format or does not provide an answer, indicating challenges with language understanding or instruction processing.	32.0%

Table 15: Breakdown of error types.

	Aya-expanse-8B	XGLM-7B	Qwen-2.5-7B	LLaMA-3.1-8B
Full Benchmark	0.02	0.17	0.13	0.29
Newly collected	0.01	0.14	0.11	0.25

Table 16: Data contamination rates per model on **INCLUDE-LITE**.