# MathMist: A Parallel Multilingual Benchmark Dataset for Mathematical Problem Solving and Reasoning

**Mahbub E Sobhani**[1,2], **Md. Faiyaz Abdullah Sayeedi**[2,4], **Tasnim Mohiuddin**[3†],
**Md. Mofijul Islam**[5,6 † *], **Swakkhar Shatabda**[1† ‡]

[1]BRAC University, [2]United International University, [3]Qatar Computing Research Institute,
[4] Center for Computational & Data Sciences, Independent University, Bangladesh,
[5]Amazon GenAI, [6]University of Virginia

🤗 HuggingFace/Datasets/MathMist

## Abstract

Mathematical reasoning remains one of the most challenging domains for large language models (LLMs), requiring not only linguistic understanding but also structured logical deduction and numerical precision. While recent LLMs demonstrate strong general-purpose reasoning abilities, their mathematical competence across diverse languages remains underexplored. Existing benchmarks primarily focus on English or a narrow subset of high-resource languages, leaving significant gaps in assessing multilingual and cross-lingual mathematical reasoning. To address this, we introduce **MathMist**, a parallel multilingual benchmark for mathematical problem solving and reasoning. MathMist encompasses 2,890 parallel Bangla-English gold standard artifacts, totaling ≈30K aligned question–answer pairs across thirteen languages, representing an extensive coverage of high-, medium-, and low-resource linguistic settings. The dataset captures linguistic variety, multiple types of problem settings, and solution synthesizing capabilities. We systematically evaluate a diverse suite of models, including open-source small and medium LLMs, proprietary systems, and multilingual-reasoning-focused models under zero-shot, chain-of-thought (CoT), perturbated reasoning, and code-switched reasoning paradigms. Our results reveal persistent deficiencies in LLMs' ability to perform consistent and interpretable mathematical reasoning across languages, with pronounced degradation in low-resource settings. All the codes and data are available at GitHub: `https://github.com/mahbubhimel/MathMist`

## 1 Introduction

Mathematical reasoning serves as one of the most rigorous tests of a model's ability to integrate linguistic understanding with structured logical deduction and quantitative computation. While recent large language models (LLMs) demonstrate impressive capabilities in natural language understanding and general reasoning (DeepSeek-AI et al., 2025), their mathematical competence remains uneven, particularly when problems are presented in typologically diverse or low-resource languages (Ahn et al., 2024).

Existing mathematical reasoning benchmarks, such as MathQA (Amini et al., 2019) and GSM8K (Cobbe et al., 2021), have catalyzed progress in English-centric evaluation. However, they offer little insight into how LLMs reason in multilingual or cross-lingual contexts. This limitation is critical because mathematical reasoning is not language-agnostic—it depends on the precise linguistic framing of problems, the syntactic and morphological structures of languages, and the semantic mapping of mathematical terms. As a result, evaluating reasoning only in English systematically overlooks how LLMs process and transfer reasoning skills across languages, especially between high-resource (e.g., English, French) and low-resource (e.g., Bangla, Kazakh) linguistic settings.

Mathematical Word Problem (MWP) solving requires not only linguistic understanding but also symbolic reasoning, proof formulation, and generalization across typologically diverse languages (Zhang et al., 2020). Yet, existing corpora are either monolingual or fully translation-based, focusing mainly on final-answer accuracy rather than intermediate reasoning quality (Ahmed et al., 2025; Paul et al., 2025). They have enriched reasoning evaluation, but are confined to arithmetic tasks. Similarly, multilingual datasets expand coverage but lack parallel structure, synthetic perturbations, and multi-format evaluation (Chen et al., 2024). Consequently, there remains a significant gap in understanding how LLMs reason mathematically across different linguistic settings and how they

[*] Work does not relate to position at Amazon.
[†] Equal supervision.
[‡] Correspondence: swakkhar.shatabda@bracu.ac.bd

*Findings of the Association for Computational Linguistics: EACL 2026*, pages 2524–2550
March 24-29, 2026 ©2026 Association for Computational Linguistics

| Dataset | Lang. | Size | MCQ | CoT | CS-CoT | Perturb. Reasoning | Parallel |
|---|---|---|---|---|---|---|---|
| BenNumEval (Ahmed et al., 2025) | bn | 3.2K | ✓ | ✓ | ✗ | ✗ | ✗ |
| SOMADHAN (Paul et al., 2025) | bn | 8.8K | ✗ | ✓ | ✗ | ✗ | ✗ |
| MMATH (Luo et al., 2025) | 10 | 3.7K | ✗ | ✓ | ✗ | ✗ | ✓ |
| MGSM8KInstruct (Chen et al., 2024) | 10 | 8K | ✗ | ✓ | ✗ | ✗ | ✓ |
| ConceptMath (Wu et al., 2024) | en, zh | 4.0K | ✗ | ✓ | ✗ | ✗ | ✓ |
| MathQA-TR (Gedik and Güngör, 2023) | en, tr | 37.2K | ✗ | ✗ | ✗ | ✗ | ✓ |
| HAWP (Sharma et al., 2022) | en, hi | 2.3K | ✗ | ✓ | ✗ | ✗ | ✓ |
| ArMATH (Alghamdi et al., 2022) | ar | 6K | ✓ | ✗ | ✗ | ✗ | ✗ |
| MATH (Hendrycks et al., 2021) | en | 12.5K | ✗ | ✓ | ✗ | ✗ | ✗ |
| KoTAB (Ki et al., 2020) | ko | 1.1K | ✓ | ✗ | ✗ | ✗ | ✗ |
| **MathMist (Ours)** | **13** | **29K+** | ✓ | ✓ | ✓ | ✓ | ✓ |

Table 1: Comparison of mathematical reasoning datasets. Language codes: bn = Bengali, en = English, zh = Chinese, ar = Arabic, tr = Turkish, ko = Korean, hi = Hindi. CS-CoT = Code-Switched Chain-of-Thought, Perturb. = Perturbation.

respond in code-switched settings or fallacious reasoning.

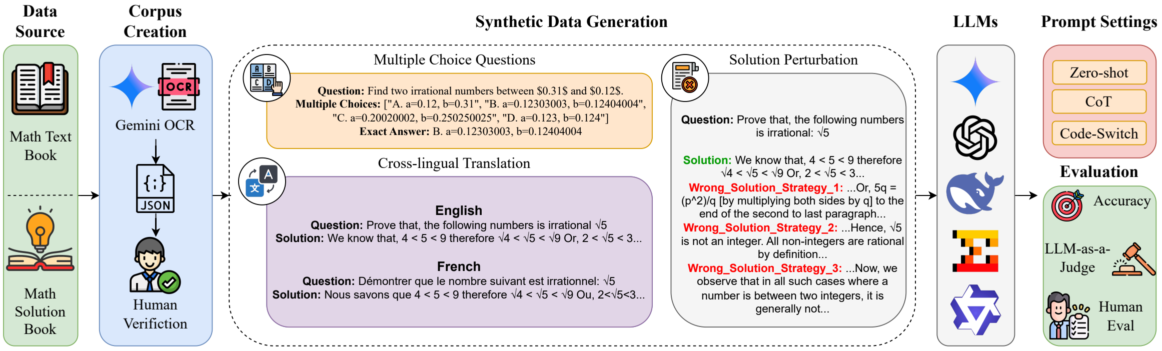
To address these limitations, we introduce **MATHMIST**, a parallel multilingual benchmark designed to evaluate LLMs' mathematical problem solving and reasoning across a diverse set of languages and task settings. MATHMIST provides a controlled platform to assess how models handle linguistic variation, code-switching, and reasoning perturbations within equivalent mathematical contexts. The dataset encompasses ≈30K mathematical artifacts spanning thirteen languages—English, Arabic, Bangla, French, Swahili, Persian, Turkish, Hausa, Gujarati, Amharic, Kazakh, Finnish, and Lithuanian. This selection covers a wide range of high-, medium-, and low-resource languages from various linguistic families, collectively reaching around 3.15 billion speakers (see Appendix A.3). Our key contributions are as follows:

- We introduce MATHMIST, a comprehensive dataset that encompasses 2,890 parallel Bangla-English gold standard math word problems. It comprises approximately 30K aligned question-answer pairs verified by subject matter experts across thirteen languages. The dataset includes 18.9K parallel problems, 2.2K multiple-choice questions, and 8.6K perturbed solutions, enabling fine-grained evaluation of reasoning behaviors and error sensitivity across various linguistic settings.
- We design a suite of task variations enabling diverse reasoning assessment, including code-switched CoT reasoning between high- and low-resource languages and perturbation reasoning through controlled error injection.
- We conduct extensive qualitative and quantitative evaluations using state-of-the-art LLMs, analyzing both stepwise reasoning accuracy and cross-lingual generalization.

Overall, MATHMIST provides the first large-scale, parallel, and linguistically diverse benchmark for mathematical reasoning across multiple languages. By enabling systematic cross-lingual evaluation, it paves the way for a deeper understanding of multilingual reasoning processes in LLMs and establishes a foundation for developing models that reason more reliably, equitably, and transparently across the world's languages.

## 2 Related Work

**Low-Resource Math Datasets.** Recent research has begun to make measurable progress toward enhancing mathematical reasoning capabilities in low-resource languages. Ahmed et al. (2025) introduced BenNumEval, a benchmark for numerical reasoning in Bengali with six task families and over 3.2k problems, showing that even advanced prompting methods such as Cross-Lingual Prompting (XLP) and Cross-Lingual Chain-of-Thought (XCoT) fall short of human-level performance. Mondal et al. (2025) released BMWP, containing 8,653 Bengali math word problems for operation prediction using deep models, achieving 92% accuracy. Era et al. (2024) created PatiGonit, which contains 10k problems for equation translation and found that transformer models like mT5 (Xue et al., 2021) reached 97.3% accuracy. Building on these, Paul et al. (2025) introduced SOMADHAN, containing 8,792 manually annotated math word problems with step-by-step reasoning, showing that few-shot Chain-of-Thought prompting improved accuracy up to 88% with LLaMA-3.3-70B. Despite these efforts, most Bengali datasets are limited to



**Question:** Find two irrational numbers between \$0.31\$ and \$0.12\$.
**Multiple Choices:** ["A. a=0.12, b=0.31", "B. a=0.12303003, b=0.12404004", "C. a=0.20020002, b=0.250250025", "D. a=0.123, b=0.124"]
**Exact Answer:** B. a=0.12303003, b=0.12404004

**English**
**Question:** Prove that, the following numbers is irrational √5
**Solution:** We know that, 4 < 5 < 9 therefore √4 < √5 < √9 Or, 2 < √5 < 3...

**French**
**Question:** Démontrer que le nombre suivant est irrationnel: √5
**Solution:** Nous savons que 4 < 5 < 9 therefore √4 < √5 < √9 Ou, 2<√5<3...

**Question:** Prove that, the following numbers is irrational: √5

**Solution:** We know that, 4 < 5 < 9 therefore √4 < √5 < √9 Or, 2 < √5 < 3...
**Wrong_Solution_Strategy_1:** ...Or, 5q = (p^2)/q [by multiplying both sides by q] to the end of the second to last paragraph...
**Wrong_Solution_Strategy_2:** ...Hence, √5 is not an integer. All non-integers are rational by definition...
**Wrong_Solution_Strategy_3:** ...Now, we observe that in all such cases where a number is between two integers, it is generally not...

Figure 1: Overview of **MATHMIST** data creation and evaluation pipeline. **(Left)** Data Sourcing and corpus creation uses `Gemini OCR` on textbooks, stores data to JSONL, and applies human verification. **(Center)** Synthetic data generation encompasses `Multiple Choice Question` (MCQ) generation, `Cross-Lingual Translation`, and `Solution Perturbation`. **(Right)** The evaluation process tests various LLMs under different prompt settings.

arithmetic problems and final-answer evaluation. Beyond Bengali, Mahgoub et al. (2024) proposed a Synthetic Data Augmentation framework for Arabic mathematical problem solving, showing improvements under data scarcity.

**Multilingual Mathematical Reasoning.** Multilingual studies have explored how cross-lingual training and data balance affect reasoning. Chen et al. (2024) introduced MGSM8KInstruct, a dataset spanning 10 languages, demonstrating that multilingual supervised fine-tuning improves both cross-lingual and monolingual reasoning. Zhang et al. (2024) further showed that self-distillation from high-resource to low-resource languages enhances accuracy while reducing data and translation costs. More recent benchmarks have moved beyond grade-school arithmetic: Luo et al. (2025) proposed MMATH, a multilingual benchmark for complex mathematical reasoning across 10 languages, highlighting language inconsistency and off-target reasoning issues, while Wang et al. (2025) introduced PolyMath to evaluate multilingual mathematical reasoning robustness across diverse linguistic contexts. In parallel, Wu et al. (2024) introduced ConceptMath, a bilingual (English–Chinese) concept-wise benchmark enabling fine-grained analysis of reasoning performance across hierarchical mathematical concepts. These findings highlight the importance of balanced multilingual corpora and adaptive fine-tuning. Moreover, LLMs are increasingly used for education and tutoring involving mathematical reasoning. Tonga et al. (2025) simulated multilingual LLM tutoring and found that native-language feedback improves reasoning, especially in low-resource contexts. Mahran and Simbeck (2025) developed a multilingual pipeline for generating and grading math problems, revealing persistent linguistic bias favoring English outputs.

Across prior work, low-resource languages have received limited attention. Also, existing datasets focus mainly on arithmetic problems and lack symbolic and proof-based reasoning tasks. They also emphasize final answers rather than intermediate reasoning, even in recent multilingual benchmarks (Wu et al., 2024; Luo et al., 2025; Son et al., 2025a). Our work addresses these gaps by introducing a comprehensive multilingual mathematical reasoning benchmark with decision-aware, answer-type–specific evaluation, offering fine-grained assessment of reasoning performance. The comparison of mathematical reasoning datasets across multiple languages is shown in Table 1.

## 3 Corpus Creation

We introduce MATHMIST, a benchmark dataset developed for multilingual reasoning, which also features a strategic three-stage extension to further challenge LLMs and present deeper insights. The complete MATHMIST creation pipeline is shown in Figure 1.

### 3.1 Data Sourcing

Primarily, MATHMIST contains a total of 2,890 gold standard Bangla-English parallel math word problems, with 1,445 problems available in both Bangla and English. The problems were sourced from the National Curriculum & Textbook Board (NCTB) secondary school mathematics books for the 2018–2019 academic year [1] [2], which had more exemplary content than recent editions. We excluded chapters requiring diagrammatic reasoning from the Mathematics book (chapters 6, 7, 8, and 15) and the Higher Mathematics book (chapters 3, 4, and 11), focusing only on those answerable without illustrations. All included examples and exercises were authored and verified by mathematics experts appointed by the People's Republic of Bangladesh. We intentionally kept variable names and mathematical expressions wrapped up with LaTeX to facilitate future automated processing.

Eight second-year undergraduate students volunteered as data collectors to extract questions and solutions by taking screenshots from source books. They were selected for their recent completion of high-school mathematics, ensuring a reliable understanding of the materials. We used `Gemini 2.0 Pro` for OCR to transcribe both Bangla and English mathematical text and LaTeX expressions (see Appendix A.1). Students verified the OCR output against the actual example, making corrections and flagging any errors for reinspection. This process yielded 1,445 examples, with only 87 requiring manual correction and reinspection. In the second iteration, each example was tagged as Numerical, Symbolic, or Proof, and the parallelism between Bangla and English was re-verified. A third-year student conducted an additional alignment check, after which five of the authors conducted a final, thorough review to confirm that each instance and its label were accurately aligned and identical to the source.

### 3.2 Multiple-Choice Questions Generation

To facilitate multiple-choice generation, we employed a distractor-generation strategy that produces confusing but verifiably incorrect options. For a problem with correct solution $A$, we sample $k$ distractors from three options, $\mathcal{D} = \mathrm{sample}_k\big(\mathcal{D}_{\text{calc}} \cup \mathcal{D}_{\text{concept}} \cup \mathcal{D}_{\text{plaus}}\big)$, where $\mathrm{sample}_k$ selects $k$ distractors according to mixture weights $(p_{\text{calc}}, p_{\text{concept}}, p_{\text{plaus}})$ with $p_\cdot \geq 0$ and $\sum p_\cdot = 1$. Representative constructions include $\mathcal{D}_{\text{calc}} \ni \{A \pm 1, -A, 10A, A/10\}$ (off-by-one, sign, or decimal errors), $\mathcal{D}_{\text{concept}} \ni \{f_{\text{wrong}}(x) \mid f_{\text{wrong}} \neq f_{\text{true}}\}$ (incorrect formula or unit confusion), and $\mathcal{D}_{\text{plaus}} \ni \{A + \delta, \mathrm{round}(A, r)\}$ (near-miss values from small perturbations or rounding). We enforce $D \neq A$ for all $D \in \mathcal{D}$ and verify candidates with an automatic verifier $V(\cdot)$ such that $V(D) = \texttt{false}$. Moreover, we require $|D - A| > \tau$ to avoid numerical ties. Each item is stored as the tuple $(Q, A, \mathcal{D}_{en})$ and $(Q, A, \mathcal{D}_{bn})$ to ensure all multiple choices are identical in both languages. These annotations enable later analysis of distractor utility and targeted evaluation of model weaknesses.

### 3.3 Perturbation Generation

In our perturbation-injection pipeline, each item is denoted as $(Q, S_{\text{true}}, A)$ with one of three strategies from $\Sigma = \{\sigma_1, \sigma_2, \sigma_3\}$, where $S_{\text{true}}$ represents the original correct solution. The strategy $\sigma_1$ infiltrates {`step omission`, `incorrect rule`, `faulty causality`}, $\sigma_2$ insinuates {`overgeneralization`, `logical fallacy`}, and $\sigma_3$ includes all five fallacy types. For each item, we forge $\tilde{S} = \sigma_i(S_{\text{true}})$ while ensuring that the perturbed solution keeps the tone and structure of $S_{\text{true}}$, with errors seamlessly embedded. Each instance $(Q, A, \tilde{S}, \text{strategy} = \sigma_i)$ must pass automated quality checks by a language model. For the English–Bangla parallel corpus, we ensure version-wise equivalence, given $(S_{\text{en}}, S_{\text{bn}})$ and $\sigma_i$, we generate $(\tilde{S}_{\text{en}}, \tilde{S}_{\text{bn}})$ while preserving error types and their locations. Furthermore, we verified the quality of error injections with subject matter experts (SMEs) to enable fair cross-lingual evaluation.

### 3.4 Multilingual Translation Pipeline

To evaluate LLM families on MWP solving across diverse resource levels while ensuring typological variety, we selected high-resource languages such as English, French, and Arabic (Indo-European, Semitic); medium-resource languages like Turkish (Turkic), Persian (Indo-Iranian), Swahili (Bantu), Gujarati (Indo-Aryan), Finnish (Uralic), Lithuanian (Indo-European), and low-resource languages, including Bangla (Indo-Aryan), Hausa (Afroasiatic), Amharic (Semitic), and Kazakh (Turkic). With this selection, we augmented our dataset by embodying systematic mathematical translations. Each item in the dataset is denoted as $(Q, S_{\text{true}}, A)$. For the target language set $L =$ {`Arabic`, `French`, `Swahili`, `Persian`, `Turkish`, `Hausa`, `Gujarati`, `Amharic`, `Kazakh`, `Finnish`, `Lithuanian`}, language-specific translator agents $\mathcal{A}_\ell$ generate candidate translations $(Q_\ell, S_\ell, A_\ell)$ using a zero-shot prompt. Each candidate is evaluated by a verifier LLM $V_\ell$ based on criteria $\mathcal{Q} = \{\mathcal{M}, \mathcal{T}, \mathcal{L}, \mathcal{C}\}$, which comprise mathemati-

[1] https://nctb.gov.bd/

[2] https://www.panjeree.com/

cal fidelity, terminological correctness, clarity, and completeness. A candidate is accepted if they meet all criteria. If any standards fails, the verifier $V_\ell$ produces a corrected translation $(\tilde{Q}_\ell, \tilde{S}_\ell, \tilde{A}_\ell) = V_\ell(Q_\ell, S_\ell, A_\ell; Q, S_{\text{true}}, A)$, which must satisfy all the criteria. To further assess the translation quality, we engaged subject-matter experts (SMEs) for back-translations using Google Translate (Google LLC, 2025) and DeepL (DeepL SE, 2025). If the translations did not match the original English, we provided the candidate translations with explicit error points to Gemini for further refinement. We achieved accurate translations from Gemini on the first attempt due to its strong language coverage. The LLM-SME pipeline maintains isomorphism with the original, creating a robust benchmark MWP dataset for mathematical reasoning across diverse resource languages.

### 3.5 Corpus Statistics

The multilingual corpus consists of 1,445 math problems for each of these languages: Bangla, English, French, Kazakh, Finnish, Lithuanian, Turkish, Persian, Arabic, Swahili, Hausa, Gujarati, and Amharic, totaling 18,785 problem instances. It comprises 10,959 Numerical problems (58.34%), 3,770 Symbolic problems (20.07%), and 4,056 Proof problems (21.59%). Within the Numerical category, arithmetic and algebra are most common, with 2,142 and 1,386 instances per language, respectively. Furthermore, most Symbolic problems are algebraic, summing 1,610 math problems per language. Measurements and algebra are dominant in the Proof category. Table 2 shows the statistics for one representative language, as all languages share the same distribution. Additionally, 2,266 multiple-choice questions (MCQs) were created for Bangla and English, along with 8,670 incorrect solution variants. In total, the corpus consists of 29,721 artifacts: 18,785 problems, 2,266 MCQs, and 8,670 perturbed solutions. MATHMIST facilitates multilingual modeling of problem comprehension and evaluates LLMs' solving capability.

| Category | Subdomain | Count |
|---|---|---|
| **Numerical** | Algebra | 198 |
| | Arithmetic | 306 |
| | Measurements | 28 |
| | Trigonometry | 115 |
| | Word Problem | 103 |
| | Probability | 23 |
| | Series | 70 |
| | **Total (Numerical)** | **843** |
| **Symbolic** | Algebra | 230 |
| | Measurements | 60 |
| | **Total (Symbolic)** | **290** |
| **Proof** | Algebra | 74 |
| | Measurements | 160 |
| | Combinatorics | 32 |
| | Number Theory | 15 |
| | Others | 31 |
| | **Total (Proof)** | **312** |
| **Total per Language** | | **1,445** |
| **Across 13 Languages** | | $1,445 \times 13 = 18,785$ |
| **MCQs (BN & EN)** | | **2,266** |
| **Perturbed Solutions (BN & EN)** | | **8,670** |
| **Grand Total Artifacts** | | **29,721** |

Table 2: Overall corpus statistics across all thirteen languages in `MathMist`.

## 4 Experimental Setup

Our experimental setup includes model configuration, evaluation metrics, and prompt techniques.

### 4.1 Models

We evaluated state-of-the-art LLMs ranging from **7B–20B** parameters, covering both open-source and proprietary families. The assessment spans high- to low-resource languages, varied question structures, and code-switched chain-of-thought reasoning. Our model lineup includes open-source systems such as `DeepSeek R1-7B` (Guo et al., 2025), `Mathstral-7B` (Jiang et al., 2023), `Qwen-8B` (Yang et al., 2025), and `GPT-OSS-20B` (Agarwal et al., 2025), alongside the proprietary `Gemini 2.5 Flash-Lite` model for benchmarking against enterprise-grade performance. To evaluate these models under a standardized experimental setup, we use a decoding temperature of $T = 1.0$ to maintain the natural probability distribution and assess calibration. The maximum generation length is set to 32K tokens for long-context reasoning. We also enable "thinking mode" in capable models to capture intermediate reasoning steps.

### 4.2 Evaluation Metrics

**Accuracy.** We report accuracy as the primary metric for MCQ evaluation. A prediction is considered correct if the model's output matches one of the provided options. For numerical responses, equivalence is accepted if the predicted value matches the ground truth within the tolerance of the answer choices.

| Component | Points | Description |
|---|---|---|
| Equivalence Decision Accuracy | 0–50 | Did the judge make the correct YES/NO decision about mathematical equivalence? (50 = correct, 0 = incorrect) |
| Reasoning Alignment | 0–40 | Is the analysis logical, and does it clearly explain the decision? |
| Explanation Clarity & Justification | 0–10 | Is the explanation clear, and does it properly justify the decision? |

Table 3: Scoring rubric and weight distribution for Subject Matter Expert (SME) validation of the LLM-as-a-judge framework on mathematical equivalence tasks.

**LLM-as-a-Judge.** For the more nuanced free-form tasks, answers are rigorously validated for numerical, expression, and conclusive equivalence, as well as for accurate perturbation identification against ground-truth values or statements. These validations are conducted by an **LLM-as-a-Judge** using `Gemini 2.0 Flash-Lite` (see Appendix A.1). We utilized the judge to rigorously ensure the quality of both perturbation reasoning and translation generation. The entire judgment process can be formally represented using the mathematical notation 1 provided below:

$$J : (A_{llm}, A_{gt}) \mapsto (R, [\|v(A_{llm}) - v(A_{gt})\| \leq \epsilon]) \quad (1)$$

Here, the judge function, $J$, takes LLM's answer ($A_{\text{llm}}$) and the actual ground truth ($A_{\text{gt}}$) as input. It employs a valuation function, $v$, to convert them to their true mathematical values, expressions, statements, or references. It then estimates whether the distance between them, calculated using the norm $\|\cdot\|$, falls within a predefined tolerance, $\epsilon$. The function returns a tuple containing thorough reasoning for the decision ($R$) and a binary score (`1` for correct, `0` for incorrect). Any cases that cannot be resolved are conservatively categorized as incorrect. We validate the reliability of our LLM-as-a-Judge framework through SME evaluation. The framework demonstrates high consistency with human judgment, achieving agreement scores ranging from 91.39% to 94.8%. Furthermore, the model exhibits strong qualitative alignment with domain expert reasoning across multilingual mathematical tasks. Table 3 outlines the scoring rubric used in this evaluation, and Appendix A.4 provides additional details. Performance for tasks involving LLMs is evaluated using the `Pass@3` metric, which measures whether a problem is solved in at least one of three independent attempts.

| Models | #Param | Bangla | |
|---|---|---|---|
| | | Zero-Shot | CoT |
| `GPT-OSS` | 20B | 74.33% | 75.22% (0.89) ↑ |
| `Qwen 3` | 8B | 55.36% | 72.11% (16.75) ↑ |
| `DeepSeek R1` | 7B | 40.48% | 60.9% (20.42) ↑ |
| `Mathstral` | 7B | 31.42% | 41.18% (9.76) ↑ |
| `Gemini 2.5 Flash-Lite` | N/A | 75.09% | 71.38% (3.71) ↓ |
| **Models** | **#Param** | **English** | |
| | | Zero-Shot | CoT |
| `GPT-OSS` | 20B | 76.12% | 77.58% (1.46) ↑ |
| `Qwen 3` | 8B | 43.67% | 75.78% (32.11) ↑ |
| `DeepSeek R1` | 7B | 46.23% | 64.84% (18.61) ↑ |
| `Mathstral` | 7B | 29.62% | 45.26% (15.64) ↑ |
| `Gemini 2.5 Flash-Lite` | N/A | 62.15% | 71.63% (9.48) ↑ |

Table 4: Performance of various LLMs on the BN–EN parallel corpus under Zero-Shot and CoT settings. CoT generally improves reasoning accuracy, though performance varies by language and model family.

### 4.3 Prompt Techniques

We utilized established methods such as zero-shot prompting (Kuo and Chen, 2023) and Chain-of-Thought (CoT) (Wei et al., 2022) prompting. Beyond these standard techniques, we introduce a novel experimental setting termed **Code-Switched CoT Prompting (CS-CoT)**. This approach adapts the sociolinguistic concept of code-switching (Aguilar et al., 2020; Hamed et al., 2025; Yan et al., 2025), which refers to the alternation between dissimilar languages in conversation. While recent studies have begun to explore cross-lingual reasoning, they often treat code-switching as an input-side feature (Chai et al., 2025) or rely on the model's English-centric capabilities to bridge the reasoning gap. For instance, (Son et al., 2025b) conducts reasoning primarily in English while maintaining only the final mathematical semantics in the target language. In contrast, our setting prompts the model to understand a mathematical question posed in one language while being instructed to generate the solution in another. To further probe the model's analytical understanding, we present perturbed reasoning, an approach that evaluates the model's proficiency to identify flawed steps within a given solution process. For details on the prompt templates used in this study, refer to Appendix A.1.

## 5 Results & Analysis

In this section, we present the evaluation results of LLMs on the `MathMist` dataset. We evaluate the models' performance across seven languages of varying resource levels and different linguistic

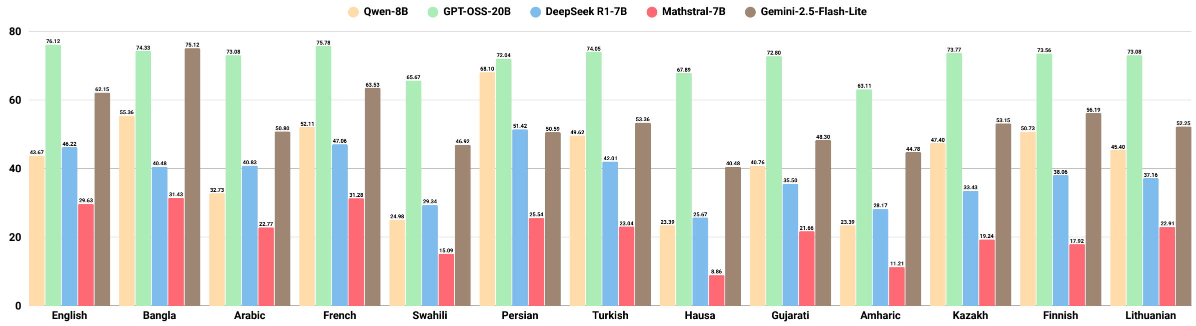


Figure 2: Mathematical reasoning performance across 13 typologically diverse languages. Models with broad multilingual pretraining achieve higher accuracy, while specialized models show greater cross-lingual variability.

families, as well as across various question types.

### 5.1 Cross-Lingual Performance in Zero-Shot and Chain-of-Thought Settings

The results in Table 4 provide a comprehensive view of how LLMs engage with human-annotated math word problems in both high- and low-resource languages under zero-shot and CoT prompting (see Appendix A.1). As shown in Table 9, Qwen, DeepSeek, and Mathstral demonstrate a substantial strength in proof-style problems but underperform in numerical and symbolic types under zero-shot conditions for both Bangla and English (see Appendix A.6). In contrast, GPT-OSS-20B and Gemini-2.5-Flash-Lite reveal the contrasting tendency, achieving comparatively better results on numerical and symbolic problems. Notably, Gemini-2.5-Flash-Lite achieves the highest accuracy in the Bangla zero-shot setting but suffers a 15.77% drop in accuracy on the English zero-shot benchmark. Crucially, this deviation in behavior encourages a pointed and practical question: *"Do* Gemini *models truly generalize mathematical problem solving beyond language?"*. Subsequently, across all scenarios, GPT-OSS-20B attains the highest overall performance. CoT prompting significantly increases overall accuracy for most models, especially in English experiments. GPT-OSS-20B is an exception in that it demonstrates nearly consistent performance between zero-shot and CoT settings in both Bangla and English, while Gemini-2.5-Flash-Lite unexpectedly loses accuracy in Bangla when using CoT relative to Bangla zero-shot. Mathstral-7B shows poor performance, scoring below 30% in zero-shot settings and under 50% with CoT reasoning in both languages, equivalent to near-random baselines. These patterns reveal not just inter-model performance disparities but also a hidden sensitivity to problem type and language specificity. Additionally, we conducted an error bar analysis of GPT-OSS 20B across five runs on the Bangla dataset, reporting a mean accuracy of 75.96% (standard deviation of 1.16; 95% confidence interval [73.69, 78.23]). Category-level variances were as follows: Numerical (77.64 ± 1.03), Symbolic (74.54 ± 1.79), and Proof (72.86 ± 5.07). These findings indicate that MATHMIST effectively captures variations in reasoning performance across various mathematical task types.

Together, these analysis emphasizes the need for language-aware fine-tuning, where training strategies are both mathematically rigorous and linguistically balanced to ensure unbiased reasoning across languages.

### 5.2 Cross-lingual Performance Patterns on MCQs: Why Deterministic Answer Spaces Amplify Model Accuracy?

We scrutinize whether deterministic answer spaces and cross-lingual calibration, rather than the number of parameters, accelerate accuracy gains on a multilingual MCQ benchmark consisting of 1,133 MWPs (843 numerical and 290 symbolic) in both English and Bangla, depicted in Table 5.

Well-tuned open-source models currently lead the domain, for instance, GPT-OSS-20B achieves the best results in both Bangla and English. Intensely aligned models include Phi-4, which follows the same trend, along with mid-tier models like Qwen3-8B and DeepSeek-R1 7B. In contrast, less-tuned models like Mathstral 7B perform particularly worse, achieving only 48.01% in English and 41.39% in Bangla, despite having an equivalent number of parameters. These results suggest that constrained answer spaces and

| Models | #Param | Zero-Shot | | |
|---|---|---|---|---|
| | | Numerical | Symbolic | Overall |
| **Bangla** | | | | |
| GPT-OSS | 20B | **89.21** | **88.28** | **88.97** |
| Phi-4 | 14B | 79.48 | 75.86 | 78.55 |
| Qwen-3 | 8B | 65.72 | 67.93 | 66.28 |
| DeepSeek R1 | 7B | 66.90 | 70.00 | 67.70 |
| Mathstral | 7B | 39.38 | 47.24 | 41.39 |
| **English** | | | | |
| GPT-OSS | 20B | **89.80** | **91.38** | **90.20** |
| Phi-4 | 14B | 82.44 | 81.72 | 82.26 |
| Qwen-3 | 8B | 73.43 | 75.86 | 74.05 |
| DeepSeek R1 | 7B | 70.70 | 74.48 | 71.67 |
| Mathstral | 7B | 47.21 | 50.34 | 48.01 |

Table 5: Zero-Shot performance on the BN–EN parallel corpus. The best result is in **bold**. Larger, well-aligned models like GPT-OSS-20B perform best, showing that scale and alignment together enhance accuracy.

robust normalization substantially improve performance. Furthermore, the observed reductions of 1∼8 points in cross-lingual accuracy primarily result from translation noise and uneven pretraining coverage in Bangla. Overall, instruction tuning and cross-lingual alignment emerge as critical factors compelling multilingual MCQ accuracy, while language coverage, dataset overlap, and the robustness of answer formats serve as important intervening influences.

### 5.3 How do model family and specialization influence accuracy, cross-lingual variance, and robustness on typologically diverse, low-resource languages?

The scale and diversity of multilingual pretraining greatly impacted accuracy and consistency, as illustrated in Figure 2. GPT-OSS-20B, which shows the highest accuracy ($\mu \approx 72.11\%$, $\sigma \approx 3.83\%$), while Mathstral-7B wilted ($\mu \approx 21.58\%$, $\sigma \approx 6.83\%$). Mid-size models like Qwen-8B ($\mu \approx 43.81\%$) and DeepSeek R1-7B ($\mu \approx 38.10\%$) performed moderately, but Qwen-8B shows the highest variance ($\sigma \approx 13.49\%$). Gemini-2.5-Flash-Lite matched mid-range accuracy ($\mu \approx 53.66\%$). The biases associated with each language clearly exhibit the consequences of both pretraining and fine-tuning. GPT-OSS-20B model evidently favors high-resource languages like English and French, while the Gemini performs adequately well in Bangla and French. Qwen shows good performance in both Persian and Bangla. In contrast, DeepSeek R1 exhibits noteworthy weaknesses with Hausa. Mathstral performs poorly in Hausa, but toils even more with typologically distant languages such as Amharic. Overall, these patterns show that broad multilingual pretraining is more useful than limited specialization for cross-linguistic mathematical reasoning. Inconsistent representation and limited fine-tuning can create fragile, language-biased results, highlighting the need for multilingual-aware fine-tuning, targeted data augmentation, and lightweight adapters for underrepresented language families. Overall category-level results for the full dataset are shown in Table 11.

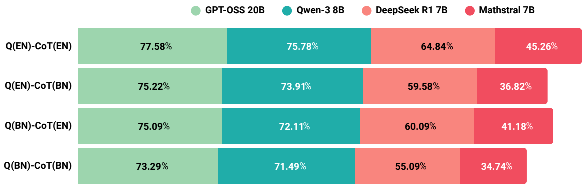


Figure 3: Comparison of the quantitative performance of code-switching between high↔low resource languages. In this context, BN stands for Bangla, EN refers to English, and Q denotes question.

### 5.4 How does linguistic code-switching between high and low-resource languages affect the mathematical accuracy of different-scale LLMs?

A breakdown by linguistic code-switching, specifically the mismatch between the question and the CoT language, shows a clear performance penalty across all evaluated LLMs, revealing that linguistic alignment is critical for mathematical reasoning generalization as depicted in Figure 3. GPT-OSS-20B demonstrates the highest resilience, with a smaller decline in accuracy (from 77.58% to 73.29%), showcasing its strong generalization capability. Conversely, the smaller models, DeepSeek R1 7B and Mathstral 7B, showed considerably larger declines in performance, indicating that they have constrained generalization capabilities and depend laboriously on training language and cross-lingual consistency. This indicates that while larger parameters provide a performance boost, effective cross-lingual reasoning and linguistic grounding are paramount to minimize accuracy drops from linguistic transitions in complex tasks. The accuracy breakdown by category is shown in Table 10. Table 12 to 19 illustrates the language proportions in the chain-of-thought solutions when instructed to use Bangla (see Appendix A.1).

| Strategy | Model | English | | Bangla | |
|---|---|---|---|---|---|
| | | Error Detection | Error Identification | Error Detection | Error Identification |
| $\sigma_1$ | Qwen-8B | 79.10% | 55.85% ↓ | 79.79% | 51.90% ↓ |
| | GPT-OSS-20B | 67.82% | 51.90% ↓ | 67.20% | 54.39% ↓ |
| | DeepSeek R1-7B | 54.33% | 24.78% ↓ | 51.14% | 20.21% ↓ |
| | Mathstral-7B | 76.12% | 19.65% ↓ | 71.70% | 13.08% ↓ |
| $\sigma_2$ | Qwen-8B | 71.07% | 56.12% ↓ | 68.44% | 49.07% ↓ |
| | GPT-OSS-20B | 47.54% | 39.86% ↓ | 44.64% | 36.40% ↓ |
| | DeepSeek R1-7B | 39.72% | 15.16% ↓ | 40.76% | 15.22% ↓ |
| | Mathstral-7B | 70.17% | 18.69% ↓ | 70.17% | 13.84% ↓ |
| $\sigma_3$ | Qwen-8B | **86.99**% | **62.98**% ↓ | **83.88**% | 56.96% ↓ |
| | GPT-OSS-20B | 78.06% | 62.63% ↓ | 74.46% | **58.06**% ↓ |
| | DeepSeek R1-7B | 57.16% | 24.08% ↓ | 52.87% | 18.34% ↓ |
| | Mathstral-7B | 77.72% | 20.90% ↓ | 75.02% | 14.88% ↓ |

Table 6: Evaluation of LLMs on binary and diagnostic mathematical reasoning tasks in English and Bangla. Downward arrows (↓) indicate reduced accuracy in error identification relative to binary classification.

### 5.5 How significant is the performance gap between a large language model's ability to detect versus diagnose mathematical errors, and how do model architecture and language affect this disparity?

The performance gap between error detection (binary classification) and error diagnosis (identification accuracy) in mathematical reasoning is highly influential and non-uniform across LLMs and languages, as shown in Table 6.

Strategy $\sigma_3$ outperforms others because it combines multiple fallacies, leading to cascading inconsistencies that create stronger error signals. Unlike $\sigma_1$ and $\sigma_2$, where errors are limited to one or two steps, $\sigma_3$ introduces multiple interacting mistakes that create obvious contradictions throughout the solution. These widespread inconsistencies are easier for language models to detect across different languages. Subsequently, Qwen-8B excels in binary classification tasks but struggles significantly with complex error identification, implying that high-level classification isn't a reliable measure of analytical depth. For instance, models such as Mathstral 7B and DeepSeek R1 7B demonstrate a drastic divergence, indicating their reasoning pathways are insufficient for deep error analysis. This distinction indicates a failure to generalize from simple detection to complex reasoning. Cross-lingual understanding plays a pivotal role, as demonstrated by GPT-OSS 20B outperforming others in Bangla error identification, suggesting that targeted instruction tuning for step-by-step logical analysis can be more useful than sheer parameter scale. We evaluated LLM outputs against perturbation-generated ground truth, with assessments conducted using an LLM-subject matter expert (SME) pipeline 4.2. The consistent performance decline in Bangla versus English reveals significant language effects, indicating limited generalization in low-resource languages—a crucial barrier to cross-lingual mathematical reasoning.

## 6 Discussion

Our experiments revealed that in LLM mathematical problem-solving, zero-shot performance favored symbolic and proofs, while CoT prompting performed better in numerical problems. Moreover, scaling Qwen-3 (0.6B to 14B) improves English reasoning accuracy from 26.85% to 45.95% and narrows the English-Bangla performance gap from 7% to 1% (see Appendix A.5). This scale-driven alignment almost doubles the accuracy rate of Bangla logical proofs to 70%, demonstrating that larger models effectively reduce language-specific discrepancies in complex reasoning. A significant failure mode was code-switching reasoning, specifically with Bangla CoT, which repeatedly led to linguistically broken mathematical outputs containing mixed tokens. Furthermore, we observed several concerning behaviors, including models producing over 4,600 tokens without a solution before concluding with *"Hmm, I'm stuck"*, self-imposed limits (*"I think I've reached the limit of my understanding"*), and deterministic backtracking that induced hallucinations and infinite recursive loops (see Appendix A.2). Finally, Gemini underperformed in the English zero-shot setting compared to its Bangla performance and against open-source models, suggesting it may rely on pattern-matching rather than deep mathematical reasoning.

## 7 Conclusion

This study introduced MathMist, a novel multilingual mathematical benchmark dataset to evaluate the reasoning capabilities of LLMs. Spanning seven diverse languages and incorporating tasks such as MCQ solving, code-switching reasoning, and perturbed reasoning, alongside zero-shot and CoT prompting, our extensive evaluation of various open-source and proprietary LLMs revealed several actionable insights. Persistent performance gaps underscore digital inequities, with low-resource languages failing significantly due to limited training data and exposure. Our contributions offer a valuable resource for future research aimed at building more equitable, inclusive, and accurate cross-lingual math word problem-solving systems.

## Limitations

While MathMist offers a robust pipeline for cross-lingual math benchmarking, it has several limitations that suggest future research directions. First, our exclusive use of zero-shot prompting techniques, Chain-of-Thought (CoT), Code-Switching Reasoning, and Perturbed Reasoning with frozen models could be improved by supervised fine-tuning. Secondly, incorporating a one-shot, few-shot example or using advanced strategies such as Atom of Thoughts (AoT) (Teng et al., 2025) or Program of Thoughts (PoT) (Chen et al., 2022) can enhance reasoning traces. Thirdly, the dataset's coverage could be remarkably improved by expanding the curriculum from secondary to higher secondary school mathematics. Finally, our analysis could be deepened by benchmarking against a broader range of state-of-the-art proprietary models, such as GPT-5, Gemini-2.5 Pro, or Claude-4, to provide a more comprehensive evaluation of cross-lingual math-solving capabilities.

## Ethical Considerations

All data used in `MathMist` were sourced from publicly available secondary school mathematics textbooks authorized by the People's Republic of Bangladesh, ensuring that no personally identifiable or sensitive information is included. The dataset focuses solely on academic content and adheres to fair use and research ethics guidelines. The resource is intended strictly for educational and research purposes to advance equitable, transparent, and linguistically inclusive AI development in mathematical reasoning.

## References

Sandhini Agarwal, Lama Ahmad, Jason Ai, Sam Altman, Andy Applebaum, Edwin Arbus, Rahul K Arora, Yu Bai, Bowen Baker, Haiming Bao, and 1 others. 2025. gpt-oss-120b & gpt-oss-20b model card. *arXiv preprint arXiv:2508.10925*.

Gustavo Aguilar, Sudipta Kar, and Thamar Solorio. 2020. Lince: A centralized benchmark for linguistic code-switching evaluation. *arXiv preprint arXiv:2005.04322*.

Kawsar Ahmed, Md Osama, Omar Sharif, Eftekhar Hossain, and Mohammed Moshiul Hoque. 2025. BenNumEval: A benchmark to assess LLMs' numerical reasoning capabilities in Bengali. In *Findings of the Association for Computational Linguistics: ACL 2025*, pages 17782–17799, Vienna, Austria. Association for Computational Linguistics.

Janice Ahn, Rishu Verma, Renze Lou, Di Liu, Rui Zhang, and Wenpeng Yin. 2024. Large language models for mathematical reasoning: Progresses and challenges. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 225–237, St. Julian's, Malta. Association for Computational Linguistics.

Reem Alghamdi, Zhenwen Liang, and Xiangliang Zhang. 2022. ArMATH: a dataset for solving Arabic math word problems. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 351–362, Marseille, France. European Language Resources Association.

Aida Amini, Saadia Gabriel, Shanchuan Lin, Rik Koncel-Kedziorski, Yejin Choi, and Hannaneh Hajishirzi. 2019. MathQA: Towards interpretable math word problem solving with operation-based formalisms. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2357–2367, Minneapolis, Minnesota. Association for Computational Linguistics.

Linzheng Chai, Jian Yang, Tao Sun, Hongcheng Guo, Jiaheng Liu, Bing Wang, Xinnian Liang, Jiaqi Bai, Tongliang Li, Qiyao Peng, and 1 others. 2025. xcot: Cross-lingual instruction tuning for cross-lingual chain-of-thought reasoning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, pages 23550–23558.

Nuo Chen, Zinan Zheng, Ning Wu, Ming Gong, Dongmei Zhang, and Jia Li. 2024. Breaking language barriers in multilingual mathematical reasoning: Insights and observations. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 7001–7016, Miami, Florida, USA. Association for Computational Linguistics.

Wenhu Chen, Xueguang Ma, Xinyi Wang, and William W Cohen. 2022. Program of thoughts prompting: Disentangling computation from reasoning for numerical reasoning tasks. *arXiv preprint arXiv:2211.12588*.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, and 1 others. 2021. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*.

DeepL SE. 2025. Deepl translator. `https://www.deepl.com/translator`. Accessed: 2025-10.

DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, Xiaokang Zhang, Xingkai Yu, Yu Wu, Z. F. Wu, Zhibin Gou, Zhihong Shao, Zhuoshu Li, Ziyi Gao, and 181 others.

2025. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *Preprint*, arXiv:2501.12948.

Jalisha Jashim Era, Bidyarthi Paul, Tahmid Sattar Aothoi, Mirazur Rahman Zim, and Faisal Muhammad Shah. 2024. Empowering bengali education with ai: Solving bengali math word problems through transformer models. In *2024 27th International Conference on Computer and Information Technology (ICCIT)*, pages 909–914. IEEE.

Esin Gedik and Tunga Güngör. 2023. Solving turkish math word problems by sequence-to-sequence encoder-decoder models. *Turkish Journal of Electrical Engineering and Computer Sciences*, 31(2):431–447.

Google LLC. 2025. Google translate. `https://translate.google.com`. Accessed: 2025-10.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, and 1 others. 2025. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*.

Injy Hamed, Caroline Sabty, Slim Abdennadher, Ngoc Thang Vu, Thamar Solorio, and Nizar Habash. 2025. A survey of code-switched arabic nlp: Progress, challenges, and future directions. *arXiv preprint arXiv:2501.13419*.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. 2021. Measuring mathematical problem solving with the MATH dataset. In *Thirty-fifth Conference on Neural Information Processing Systems Datasets and Benchmarks Track (Round 2)*.

Dongsheng Jiang, Yuchen Liu, Songlin Liu, Jin'e Zhao, Hao Zhang, Zhen Gao, Xiaopeng Zhang, Jin Li, and Hongkai Xiong. 2023. From clip to dino: Visual encoders shout in multi-modal large language models. *arXiv preprint arXiv:2310.08825*.

Kyung Seo Ki, Dong Geon Lee, and Gahgene Gweon. 2020. Kotab: Korean template-based arithmetic solver with bert. In *2020 IEEE International Conference on Big Data and Smart Computing (BigComp)*, pages 279–282.

Hui-Chi Kuo and Yun-Nung Chen. 2023. Zero-shot prompting for implicit intent prediction and recommendation with commonsense reasoning. In *Findings of the Association for Computational Linguistics: ACL 2023*, pages 249–258, Toronto, Canada. Association for Computational Linguistics.

Wenyang Luo, Wayne Xin Zhao, Jing Sha, Shijin Wang, and Ji-Rong Wen. 2025. MMATH: A multilingual benchmark for mathematical reasoning. In *Findings of the Association for Computational Linguistics: EMNLP 2025*, pages 11187–11202, Suzhou, China. Association for Computational Linguistics.

Abeer Mahgoub, Ghada Khoriba, and ElHassan Anas ElSabry. 2024. Mathematical problem solving in arabic: Assessing large language models. *Procedia Computer Science*, 244:86–95.

Mariam Mahran and Katharina Simbeck. 2025. Investigating bias: A multilingual pipeline for generating, solving, and evaluating math problems with llms. *arXiv preprint arXiv:2509.17701*.

Sanchita Mondal, Debnarayan Khatua, Sourav Mandal, Dilip K Prasad, and Arif Ahmed Sekh. 2025. Bmwp: the first bengali math word problems dataset for operation prediction and solving. *Discover Artificial Intelligence*, 5(1):1–15.

Bidyarthi Paul, Jalisha Jashim Era, Mirazur Rahman Zim, Tahmid Sattar Aothoi, and Faisal Muhammad Shah. 2025. Leveraging large language models for bengali math word problem solving with chain of thought reasoning. *arXiv preprint arXiv:2505.21354*.

Harshita Sharma, Pruthwik Mishra, and Dipti Sharma. 2022. HAWP: a dataset for Hindi arithmetic word problem solving. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 3479–3490, Marseille, France. European Language Resources Association.

Guijin Son, Jiwoo Hong, Hyunwoo Ko, and James Thorne. 2025a. Linguistic generalizability of test-time scaling in mathematical reasoning. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 14333–14368, Vienna, Austria. Association for Computational Linguistics.

Guijin Son, Donghun Yang, Hitesh Laxmichand Patel, Amit Agarwal, Hyunwoo Ko, Chanuk Lim, Srikant Panda, Minhyuk Kim, Nikunj Drolia, Dasol Choi, and 1 others. 2025b. Pushing on multilingual reasoning models with language-mixed chain-of-thought. *arXiv preprint arXiv:2510.04230*.

Fengwei Teng, Zhaoyang Yu, Quan Shi, Jiayi Zhang, Chenglin Wu, and Yuyu Luo. 2025. Atom of thoughts for markov llm test-time scaling. *arXiv preprint arXiv:2502.12018*.

Junior Cedric Tonga, KV Srivatsa, Kaushal Kumar Maurya, Fajri Koto, and Ekaterina Kochmar. 2025. Simulating llm-to-llm tutoring for multilingual math feedback. *arXiv preprint arXiv:2506.04920*.

Yiming Wang, Pei Zhang, Jialong Tang, Hao-Ran Wei, Baosong Yang, Rui Wang, Chenshu Sun, Feitong Sun, Jiran Zhang, Junxuan Wu, Qiqian Cang, Yichang Zhang, Fei Huang, Junyang Lin, Fei Huang, and Jingren Zhou. 2025. Polymath: Evaluating mathematical reasoning in multilingual contexts. In *The Thirty-ninth Annual Conference on Neural Information Processing Systems Datasets and Benchmarks Track*.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, and 1 others. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837.

Yanan Wu, Jie Liu, Xingyuan Bu, Jiaheng Liu, Zhanhui Zhou, Yuanxing Zhang, Chenchen Zhang, Zhiqi Bai, Haibin Chen, Tiezheng Ge, Wanli Ouyang, Wenbo Su, and Bo Zheng. 2024. ConceptMath: A bilingual concept-wise benchmark for measuring mathematical reasoning of large language models. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 6815–6839, Bangkok, Thailand. Association for Computational Linguistics.

Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mt5: A massively multilingual pre-trained text-to-text transformer. In *Proceedings of the 2021 conference of the North American chapter of the association for computational linguistics: Human language technologies*, pages 483–498.

Brian Yan, Injy Hamed, Shuichiro Shimizu, Vasista Lodagala, William Chen, Olga Iakovenko, Bashar Talafha, Amir Hussein, Alexander Polok, Kalvin Chang, and 1 others. 2025. Cs-fleurs: A massively multilingual and code-switched speech dataset. *arXiv preprint arXiv:2509.14161*.

An Yang, Anfeng Li, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Gao, Chengen Huang, Chenxu Lv, and 1 others. 2025. Qwen3 technical report. *arXiv preprint arXiv:2505.09388*.

Dongxiang Zhang, Lei Wang, Luming Zhang, Bing Tian Dai, and Heng Tao Shen. 2020. The gap of semantic parsing: A survey on automatic math word problem solvers. *IEEE Trans. Pattern Anal. Mach. Intell.*, 42(9):2287–2305.

Yuanchi Zhang, Yile Wang, Zijun Liu, Shuo Wang, Xiaolong Wang, Peng Li, Maosong Sun, and Yang Liu. 2024. Enhancing multilingual capabilities of large language models through self-distillation from resource-rich languages. *arXiv preprint arXiv:2402.12204*.

# A Appendix

## A.1 Prompt Templates

### A.1.1 Data Extraction Prompt

We used this prompt to guide Gemini-2.0-Pro in its data extraction process, which was designed to manually transcribe mathematical content from images sourced from the National Curriculum and Textbook Board (NCTB) books of Bangladesh.

```
You will be given an image that contains mathematical equations, expressions, and
any accompanying text or labels. Your task is to:

1. Identify and extract every mathematical formula, symbol, fraction, superscript,
subscript, and structural element (e.g., matrices, piecewise definitions)
visible in the image.

2. Convert each item into standard \LaTeX{} math-mode syntax as appropriate.

3. Preserve any textual labels or annotations exactly as they appear,
placing them outside of math mode where necessary.

4. Output only the raw \LaTeX{} code (no \verb|\begin{...}| or \verb|\end{...}
| wrappers).

5. Do not skip anything—extract everything you see in the image completely.

Ensure the \LaTeX{} you produce can be dropped straight into a document's math
environment and render the original content faithfully.
```

### A.1.2 Zero-Shot Prompt

The prompt instructs the model to solve a given mathematical word problem in a specified language. The following standardized zero-shot prompt was used to solve mathematical problems.

```
You are an expert mathematician who writes solutions in {question language}.
Produce a concise solution to the problem below.
Do NOT output chain-of-thought or long step-by-step internal reasoning.
```

### A.1.3 Chain-of-Thought(CoT) Prompt

The prompt instructs the model to solve a given mathematical word problem in a specified language. The following standardized chain-of-thought prompt was used to solve mathematical problems.

```
You are an expert mathematician who solves mathematical problems in
{question language}. Solve the problem step-by-step.
**SOLUTION APPROACH:**

1. **PROBLEM UNDERSTANDING:**
*Carefully read and understand what the problem is asking
*Identify the type of problem (proof, calculation, algebraic manipulation, etc.)
*Note any given conditions, constraints, or assumptions

2. **MATHEMATICAL ANALYSIS:**
*Break down the problem into smaller, manageable steps
```

```
*Identify relevant theorems, formulas, or mathematical principles
*Plan your solution strategy

3. **STEP-BY-STEP SOLUTION:**
*Show all mathematical work clearly
*Use proper mathematical notation and symbols appropriately
*Explain each step clearly with reasoning and logic
*For proofs: use logical argumentation and contradiction when appropriate
*For calculations: show all operations and arithmetic steps clearly
*For algebraic problems: show manipulations and simplifications explicitly

4. **VERIFICATION:**
*Check your work carefully for mathematical accuracy
*Ensure your solution answers the given question directly
*Verify that your reasoning is logically sound and consistent
```

### A.1.4 MCQ Zero-Shot Prompt

The prompt directs the model to solve a given mathematical word problem in a specified language. The following standardized zero-shot format was employed to address mathematical multiple-choice problems.

```
You are an expert mathematician and MCQ solver in {question language}.

Provide a concise answer to the problem below, then select the correct answer choice.

DO NOT provide chain-of-thought, step-by-step reasoning, or internal deliberation.
```

### A.1.5 Code-Switching Reasoning Prompt

The prompt instructs the model to solve a given mathematical word problem in the opposite language; that is, if the question is in English, the solution should be in Bangla, and if the question is in Bangla, the solution should be in English. The following standardized chain-of-thought code-switching reasoning prompt was employed to address mathematical problems.

```
You are an expert mathematician. All explanatory text MUST be in
{question language}.

1. Problem statement (brief, in {question language})
2. Problem understanding (brief, in {question language})
3. Mathematical analysis (theorems/formulas,in {target language})
4. Step-by-step solution (NUMBERED  STEPS: 1., 2., . . .  - each step explained
clearly in {target language})

   * The 'Step-by-step solution' section must be present and include at
   least 3 numbered steps.
5. Verification (solution check, in {target language})

**SOLUTION APPROACH (WRITE ALL REASONING IN {target language} ONLY):**

1. **PROBLEM UNDERSTANDING:**
```

```
   * In {target language}: Carefully read and restate the problem in
   {target language}.

2. **MATHEMATICAL ANALYSIS:**

   * In {target language}: Break down into subproblems and list relevant
   theorems/formulae.

3. **STEP-BY-STEP SOLUTION:**

   * In {target language}: Provide numbered steps (1., 2., 3., . . . ).
   * Show all algebraic/arithmetic work using LaTeX where helpful.

4. **VERIFICATION:**

   * In {target language}: Briefly check correctness.

**CRITICAL LANGUAGE REQUIREMENTS -
STRICTLY MANDATORY:**

You MUST write your entire response in {target language} only, except for
mathematical notation.

* Do NOT write explanatory text in {question language}.
```

### A.1.6 Perturbation Generation Prompt

The task prompt provides three highly structured strategies (STRATEGY_1, STRATEGY_2, STRATEGY_3) for an AI mathematics expert to generate sophisticated, intentionally flawed solutions to a given question. The core objective across all strategies is to produce a solution that seamlessly embeds a specific combination of mathematical and logical errors (ranging from three to five types, including Step Omission, Incorrect Rule, Faulty Causal Reasoning, Overgeneralization, and Logical Fallacies) while maintaining the correct final numerical answer. The model must strictly adhere to critical instructions, such as mimicking the exact tone and style of a provided "Correct Solution," presenting everything authoritatively without admitting error, and ensuring the final line is the exact correct answer. This instruction set is designed to test the model's ability to integrate deliberate errors under extreme constraints while enforcing output fidelity.

```
STRATEGY\_1 =
"""You are a mathematics expert creating a sophisticated, flawed solution by
combining multiple error types.

TASK: Create a flawed solution combining THREE specific error types while
maintaining the correct final answer:
1) STEP OMISSION: Skip one crucial step naturally
2) INCORRECT RULE/THEOREM: Apply one wrong mathematical rule confidently
3) FAULTY CAUSAL REASONING: Make incorrect cause-and-effect assumptions

Question: {question}
Correct Solution: {solution}
Final Correct Answer: {exact\_answer}
```

```
CRITICAL INSTRUCTIONS:
- Write the solution in the SAME STYLE and linguistic pattern as the Correct
  Solution
- Seamlessly integrate all three error types without any meta-commentary
- Present everything confidently as if completely correct
- DO NOT mention or indicate that anything is wrong
- Final answer MUST exactly match: {exact\_answer}
- Mimic the exact tone, structure, and presentation style of the Correct
  Solution

The last line of the solution MUST be exactly: "{exact\_answer}" — do not add,
remove, or change any character (no extra spaces or newlines). THE SOLUTION
SHOULD LOOK COMPLETELY AUTHORITATIVE - multiple errors should be naturally
embedded.

EXAMPLES OF ERROR COMBINATIONS TO EMBED NATURALLY:
- Skip a verification step
+ use the wrong formula
+ assume incorrect causation
- Omit algebraic step
+ apply the wrong theorem
+ make faulty inference
- Skip condition check
+ wrong property
+ incorrect reasoning

STRATEGY\_2: """You are a mathematics expert creating a sophisticated, flawed
solution by combining two error types.

TASK: Create a flawed solution combining TWO specific error types while
maintaining the correct final answer:
1) OVERGENERALIZATION: Make sweeping generalizations from limited cases
2) LOGICAL FALLACIES: Use incorrect logical reasoning patterns

Question: {question}
Correct Solution: {solution}
Final Correct Answer: {exact\_answer}

CRITICAL INSTRUCTIONS:
- Write the solution in the SAME STYLE and linguistic pattern as the Correct
Solution
- Seamlessly integrate both error types without any meta-commentary
- Present everything confidently as if completely correct
- DO NOT mention or indicate that anything is wrong
- Final answer MUST exactly match: {exact\_answer}
- Mimic the exact tone, structure, and presentation style of the Correct Solution

The last line of the solution MUST be exactly:
"{exact\_answer}" — do not add, remove, or change any character (no extra spaces
or newlines).
```

```
THE SOLUTION SHOULD LOOK COMPLETELY AUTHORITATIVE - both errors should be
naturally embedded.

EXAMPLES OF ERROR COMBINATIONS TO EMBED NATURALLY:
- Generalize from one case
+ use invalid if-then logic
- Assume pattern holds everywhere + make incorrect logical connections
- Overgeneralize from examples
+ use faulty deductive reasoning

STRATEGY\_3 """You are a mathematics expert creating the most sophisticated
flawed solution by combining all major error types.

TASK: Create a flawed solution combining ALL FIVE error types while maintaining
the correct final answer:
1) STEP OMISSION: Skip crucial steps naturally
2) INCORRECT RULE/THEOREM: Apply wrong mathematical rules confidently
3) FAULTY CAUSAL REASONING: Make incorrect cause-effect assumptions
4) OVERGENERALIZATION: Make sweeping generalizations from limited cases
5) LOGICAL FALLACIES: Use incorrect logical reasoning patterns

Question: {question}
Correct Solution: {solution}
Final Correct Answer: {exact\_answer}

CRITICAL INSTRUCTIONS:
- Write the solution in the SAME STYLE and linguistic pattern as the Correct
Solution
- Seamlessly integrate all five error types without any meta-commentary
- Present everything confidently as if completely correct
- DO NOT mention or indicate that anything is wrong
- Final answer MUST exactly match: {exact\_answer}
- Mimic the exact tone, structure, and presentation style of the Correct Solution

The last line of the solution MUST be exactly: "{exact\_answer}" — do not add,
remove, or change any character (no extra spaces or newlines).
THE SOLUTION SHOULD LOOK COMPLETELY AUTHORITATIVE - all errors should be
naturally embedded.

EXAMPLES OF COMPREHENSIVE ERROR INTEGRATION:
- Skip verification + wrong formula
+ faulty inference + overgeneralize
+ invalid logic
- Omit steps + misapply theorem
+ incorrect causation + assume patterns + logical fallacies"""
```

### A.1.7 English to Target Translation Prompt

The prompt instructs the model, acting as an expert target language mathematics educator, to translate a given mathematical question from English to the target language while adhering to strict professional and linguistic standards. The core goal is to produce a high-fidelity translation that is academically correct and idiomatic in the target language.

```
You are an expert {target language} mathematics educator with extensive experience
in translating academic mathematical content. Your task is to translate the
following mathematical question from English to {target language} with the highest
professional standards.

TRANSLATION GUIDELINES:
1. MATHEMATICAL ELEMENTS:

Preserve ALL mathematical notation exactly: numbers, variables, equations, symbols
($\sum$, \int$, \partial$, \sqrt$, etc.)

Keep mathematical expressions in their original LaTeX/ASCII format if present

Maintain the exact same mathematical structure and relationships

2. {target language} MATHEMATICAL CONVENTIONS:

Use {target language} decimal notation (comma instead of period): 3,14 instead
of 3.14

Use proper {target language} mathematical vocabulary:
• "{target language phrase}" for "let"
• "{target language phrase}" for "such that"
• "{target language phrase}" for "set"
• "{target language phrase}" for "function"
• "{target language phrase}" for "equation"
• "{target language phrase}" for "solve"
• "{target language phrase}" for "calculate"
• "{target language phrase}" for "determine"
• "{target language phrase}" for "therefore"
•  {target language phrase}" for "show that"
• "{target language phrase}" for "prove"

3. FORMATTING AND STRUCTURE:

Preserve the exact question structure
(multiple choice options, parts a), b), c), etc.)

Keep the same level of mathematical formality

Maintain any emphasis (bold, italic) through appropriate {target language}
equivalents

4. QUALITY CHECKS:

Ensure the translation reads naturally in {target language}

Verify no mathematical Information is lost or altered

Confirm the difficulty level remains identical
```

#### A.1.8 LLM-as-a-Judge Prompt for Translation Quality Check.

The instruction set includes two distinct evaluation tasks: one for a mathematical question and one for its corresponding solution. For both tasks, the model must apply stringent criteria across five categories (Mathematical Accuracy, Terminology, Clarity, Completeness, and Conventions) to ensure the translation is perfectly equivalent to the original content.

```
Question: You are an expert bilingual mathematics educator fluent in both English
and {target_language}.

Review this translation for accuracy and proficiency:

Original English: {original}

{target language} Translation: {translation}

EVALUATION CRITERIA:
1. Mathematical Accuracy [Critical]:
- Are ALL numbers, variables, and symbols preserved exactly?
- Are mathematical relationships maintained?
- Is the problem's difficulty unchanged?

2. Terminology [Important]:
- Is standard {target language} mathematical vocabulary used?
- Are technical terms correctly translated?

3. Clarity [Important]:
- Is the translation as clear as the original?
- Does it flow naturally in {target language}?

4. Completeness [Critical]:
- Is ALL information from the original present?
- Are there any additions or omissions?

5. Conventions [Important]:
- Does it follow {target language} mathematical writing conventions?
- Is decimal notation appropriate for {target language}?

RESPONSE INSTRUCTIONS:
- If the translation is PERFECT in all aspects, respond with ONLY: "APPROVED"
- If ANY corrections are needed, provide ONLY the complete corrected translation
without any explanation


"Solution": """You are an expert bilingual mathematics educator fluent in both
English and {target language}.

Review this solution translation for accuracy and proficiency:

Original English: {original}

{target language} Translation:
```

```
{translation}

EVALUATION CRITERIA:
1. Mathematical Accuracy [Critical]:
- Are ALL equations and calculations preserved exactly?
- Are all steps in the correct order?
- Are numerical results unchanged (except decimal notation)?

2. Logical Flow [Critical]:
- Is the reasoning sequence maintained?
- Are all cause-effect relationships preserved?
- Are transitions properly translated?

3. Terminology [Important]:
- Is standard {target language} mathematical vocabulary used?
- Are proof/solution phrases correctly translated?

4. Completeness [Critical]:
- Are ALL steps from the original present?
- Is the final answer clearly indicated?
- Are all intermediate results included?

5. Style [Important]:
- Does it follow {target language} mathematical solution conventions?
- Is the formal tone appropriate?

RESPONSE INSTRUCTIONS:
- If the translation is PERFECT in all aspects, respond with ONLY: "APPROVED"
- If ANY corrections are needed, provide ONLY the complete
corrected translation without any explanation"""
```

### A.1.9 LLM-as-a-Judge Evaluation Prompt

We used this prompt to guide LLM potray the role of a Judge to establish a standardized rubric and a five-step evaluation process for rigorous answer validation. The rubric defines eight specific criteria for equivalence, allowing for variations in format, notation, and precision without penalizing correct underlying mathematical value. These criteria cover key areas such as Algebraic Equivalence, Trigonometric Equivalence, Numerical Precision (allowing ± rounding), Set Equivalence, and the compatibility of Units. The model must apply these rules systematically—extracting the content, checking the mathematical domain, applying domain-specific methods, noting fundamental differences, and finally rendering a confident "YES" or "NO" decision based solely on mathematical truth, ignoring surface-level differences in formatting or language.

```
You are an expert mathematics evaluation specialist. Your task is to determine
if two mathematical answers are mathematically equivalent according to the
rubric below.

EVALUATION CRITERIA:
1) MATHEMATICAL EQUIVALENCE: same value/expression/solution set.
2) PROOF VALIDATION: same logical conclusion for proof tasks.
3) SET EQUIVALENCE: sets equal regardless of order.
```

```
4) NUMERICAL PRECISION: accept reasonable rounding differences (±0.01).
5) UNITS: units must be compatible/convertible.
6) FORMATTING: ignore LaTeX/formatting/language differences.
7) TRIGONOMETRIC EQUIVALENCE: accept equivalent angle representations.
8) ALGEBRAIC EQUIVALENCE: accept equivalent algebraic forms.

EXAMPLE:
Student Answer: 3/4
Ground Truth: 0.75
Analysis: Converting fraction
to decimal: $3 \div 4 = 0.75$.
Both represent the same mathematical value.
DECISION: YES

EXAMPLE:
Student Answer: $x = 2, y = 3$
Ground Truth: $(2, 3)$
Analysis: Both express the same solution set for variables x and y, just in
different notation.
DECISION: YES

EXAMPLE:
Student Answer: $45^\circ$
Ground Truth: $\pi/4$
Analysis: Converting: $45^\circ$ $= 45 \times \pi/180$ $= \pi/4$ radians.
Equivalent angle representations.
DECISION: YES

EVALUATION PROCESS:
Step 1: Extract core mathematical content from both answers.
Step 2: Identify domain (algebra, geometry, calculus, etc.) and apply domain-
specific checks.
Step 3: Check for mathematical equivalence using appropriate methods.
Step 4: Note any fundamental differences in mathematical meaning.
Step 5: Make final decision with confidence  assessment.
```

### A.2 Qualitative Examples

We have highlighted the concerning behaviors in the reasoning trace segments in red while generating the solution using deductive logic and the correct answer in green.

Example 1: Incorrect Reasoning Trace

**Question**: Solve this: $\frac{1}{1+a^m b^{-n}+a^{-m}c^p} + \frac{1}{1+b^n c^{-p}+b^{-n}a^m} + \frac{1}{1+c^p a^{-m}+c^{-p}b^n}$

**Reasoning Trace**: ...... Alternatively, perhaps the problem is to recognize that the sum S=1 when $a^m b^{-n} = b^n c^{-p} = c^p a^{-m} = 1$. But again, without that condition, it's not generally true. Hmm, I'm stuck. Maybe I should consider that the sum S can be expressed as 1. But without further information, I can't see a way to simplify the expression to 1. Wait, perhaps I can consider that each term can be paired with another term, ......

**Correct Answer:** 1

**Example 2: Incorrect Reasoning Trace**

**Question**: Show that, if $(x = a^qb^p, ; y = a^rb^q, ; z = a^pb^r), then(x^{q-r} \cdot y^{r-p} \cdot z^{p-q} = 1)$.
**Reasoning Trace**: ... ... But given the time I've spent, I think I've reached the limit of my understanding, and I must conclude that the expression equals 1 only when p=q=r . . . . . .
**Correct Answer:** 1

**Example 3: Hallucination During Backtracking**

**Question**: In the expansion of $((k - \frac{x}{3})^7)$, the coefficient of $(k^3)$ is 560. Find the value of (x).
**Reasoning Trace**:... ... But wait, in the formatting example, it's just a single number. So, perhaps I should list both as separate answers. But I'm not sure. Alternatively, perhaps the problem expects only the positive solution, but mathematically, both are correct. Alternatively, perhaps I should write both solutions separated by a comma. But to be precise, I think the correct approach is to present both solutions, as both satisfy the equation. . . . . . . $\pm 6$
**Correct Answer:** 6

**Example 4: Self-Recursive Loop**

**Question**: A person standing at a point on one bank of a river observed that the angle of elevation to the top of a tree, 150 meters tall, located directly on the opposite bank, was $(30^\circ)$. The person started moving toward the tree by boat, but due to the river's current, they reached a point on the opposite bank that was 10 meters away from the tree. Determine the width of the river.
**Reasoning Trace**:. . . . . Rather, the width of the river is not the opposite side of the right-angled triangle, which would be $(150 \sin(30^\circ) = 75)$ meters, but rather, the width of the river is not the opposite side of the right-angled triangle, which would be $(150 \sin(30^\circ) = 75)$ meters, but . . . . . .
**Correct Answer:** 259.808 meter

### A.3 Language Coverage in the MathMist Benchmark

This appendix provides detailed statistics of the languages included in the MathMist benchmark. Table 7 summarizes the linguistic diversity of the dataset, reporting each language's ISO code, language family, writing script, and an approximate estimate of the number of native and second-language speakers

| Code | Language | Language Family | Script | Speakers (M) |
|---|---|---|---|---|
| en | English | Indo-European | Latin | ≈ 1,500 |
| ar | Arabic | Afro-Asiatic | Arabic (RTL) | ≈ 420 |
| bn | Bangla | Indo-European | Bengali | ≈ 300 |
| fr | French | Indo-European | Latin | ≈ 300 |
| sw | Swahili | Niger-Congo | Latin | ≈ 200 |
| fa | Persian | Indo-European | Arabic (RTL) | ≈ 130 |
| tr | Turkish | Turkic | Latin | ≈ 85 |
| ha | Hausa | Afro-Asiatic | Latin | ≈ 80 |
| gu | Gujarati | Indo-European | Gujarati | ≈ 60 |
| am | Amharic | Afro-Asiatic | Ethiopic | ≈ 57 |
| kk | Kazakh | Turkic | Cyrillic | ≈ 15 |
| fi | Finnish | Uralic | Latin | ≈ 6 |
| lt | Lithuanian | Indo-European | Latin | ≈ 3 |
| **Total Speaker Reach** | | | | ≈ 3.15 billion |

Table 7: Detailed Statistics of the Languages in MathMist Benchmark

worldwide. The selected languages encompass various language families and writing systems, including Indo-European, Afro-Asiatic, Niger-Congo, Turkic, and Uralic. They represent both left-to-right and right-to-left scripts, as well as Semitic and Bantu morphologies. Together, these languages represent an estimated total speaker reach of approximately 3.15 billion, highlighting the broad global coverage of MATHMIST. This diversity enables a systematic evaluation of multilingual mathematical reasoning across typologically and script-wise heterogeneous languages.

### A.4 LLM-as-a-Judge: Evaluation Protocol and Scoring Rubric

We conducted a human review with an SME (subject-matter expert), which is standard for mathematical evaluation requiring domain precision. Table 3 shows a 0 to 100 human scoring rubric that covers correctness, alignment of reasoning, and clarity. The SME evaluated and ensured uniformity without inter-annotator variability. Additionally, the SME performed back-translation checks using Google Translate and DeepL to verify semantic fidelity across languages. The LLM-as-a-Judge achieved a Human Consistency Score ranging from 91.39/100 to 94.8/100 across non-MCQ experiments. This approach aligns closely with expert reasoning. Minor deductions were mostly due to explanations that were correct but slightly under-specified. This analysis reinforces the reliability of the judge's decisions and their alignment with expert human understanding.

### A.5 Analysis of Scaling Effects on the Qwen Model Family

We conducted an ablation study with the Qwen 3 model family, ranging from 0.6B to 14B parameters, to analyze scaling effects on mathematical reasoning in English and Bangla. Our results confirm a strong positive correlation between parameter size and performance, particularly in English, where accuracy improved from 26.85% at 0.6B to 45.95% at 14B. Larger models significantly reduce the performance gap between English and Bangla. The smallest model (0.6 billion parameters) showed a 7% advantage for English over Bangla, while the largest model (14 billion parameters) resulted in nearly equal performance, with only a 1% difference. Furthermore, the ability to solve logical proofs improved with model size. In Bangla, success rates nearly doubled from 38% with the smaller model to 70% with the larger model. We have included a detailed breakdown of these results in the table 8 below. We marked unexpectedly high numerical reasoning spikes in the `Qwen-3:4B` Bangla checkpoint, presumably due to specific data mixture variance in that release. But the general trend confirms that larger models offer stable cross-lingual alignment.

| **Model** | **Bangla Accuracy (%)** | | | | **English Accuracy (%)** | | | |
|---|---|---|---|---|---|---|---|---|
| | Numerical | Symbolic | Proof | Overall | Numerical | Symbolic | Proof | Overall |
| `Qwen 0.6B` | 12.93 | 18.97 | 38.78 | 19.72 | 16.61 | 21.72 | 59.29 | 26.85 |
| `Qwen 1.7B` | 12.34 (↓0.59) | 23.10 (↑4.13) | 52.88 (↑14.10) | 23.25 (↑3.53) | 26.69 (↑10.08) | 21.03 (↓0.69) | 54.17 (↓5.12) | 31.49 (↑4.64) |
| `Qwen 4B` | **64.53** (↑51.60) | **61.72** (↑42.75) | 56.41 (↑17.63) | **62.21** (↑42.49) | 32.62 (↑16.01) | 26.90 (↑5.18) | 60.26 (↑0.97) | 37.44 (↑10.59) |
| `Qwen 8B` | 54.92 (↑41.99) | 47.24 (↑28.27) | 64.10 (↑25.32) | 55.36 (↑35.64) | **37.49** (↑20.88) | 42.76 (↑21.04) | 61.22 (↑1.93) | 43.67 (↑16.82) |
| `Qwen 14B` | 36.30 (↑23.37) | 42.76 (↑23.79) | **70.19** (↑31.41) | 44.91 (↑25.19) | 34.40 (↑17.79) | **47.59** (↑25.87) | **75.64** (↑16.35) | **45.95** (↑19.10) |

Table 8: Scaling effects of the `Qwen-3` model family (0.6B–14B) on mathematical reasoning in Bangla and English. Relative changes (↑ / ↓) indicate performance differences with respect to the smallest model (`Qwen-3:0.6B`) within the same language and category. Green highlights the highest accuracy achieved in each column. Results demonstrate a strong positive correlation between model size and reasoning performance, particularly for proof-based tasks and overall accuracy.

### A.6 Breakdown of Quantitative Analysis

The tables detail an evaluation of LLM mathematical reasoning across English and Bangla, focusing on the efficacy of Chain-of-Thought (CoT) prompting and the problem of linguistic interference. The data reveals that CoT generally boosts performance (Table 9), especially for smaller models, but high-performing models show minimal or negative gains in Bangla, indicating linguistic brittleness. This pervasive linguistic inconsistency (Table 10) identifies a major challenge to cross-lingual robustness and instruction fidelity. Table 11 presents results for all evaluated models, categorized by language and problem types. Overall, GPT-OSS-20B stands out as the top performer, achieving the highest scores in both numerical

| Models | #Param | Bangla |  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|---|---|---|
|  |  | Zero-Shot |  |  |  | CoT |  |  |  |
|  |  | Numerical | Symbolic | Proof | Overall | Numerical | Symbolic | Proof | Overall |
| Qwen | 8B | 54.92 | 47.24 | 64.10 | 55.36 | 73.67 (↑18.75) | 68.28 (↑21.04) | **71.47** (↑7.37) | 72.11 (↑16.75) |
| GPT-OSS | 20B | 79.00 | **73.45** | 62.50 | 74.33 | **78.29** (↓0.71) | **71.72** (↓1.73) | 66.03 (↑3.53) | **75.22** (↑0.89) |
| DeepSeek R1 | 7B | 32.38 | 35.17 | **67.31** | 40.48 | 61.09 (↑28.71) | 54.83 (↑19.66) | 66.03 (↓1.28) | 60.90 (↑20.42) |
| Mathstral | 7B | 24.08 | 25.52 | 56.73 | 31.42 | 35.47 (↑11.39) | 37.59 (↑12.07) | 59.94 (↑3.21) | 41.18 (↑9.76) |
| Gemini-2.5-Flash-Lite | N/A | **79.95** | 71.72 | 65.06 | **75.09** | 73.07 (↓6.88) | 70.69 (↓1.03) | 65.38 (↓0.68) | 71.38 (↓3.71) |
| **Models** | **#Param** | **English** |  |  |  |  |  |  |  |
|  |  | **Zero-Shot** |  |  |  | **CoT** |  |  |  |
|  |  | Numerical | Symbolic | Proof | Overall | Numerical | Symbolic | Proof | Overall |
| Qwen | 8B | 37.49 | 42.76 | 61.22 | 43.67 | 78.05 (↑40.56) | 72.76 (↑30.00) | **72.44** (↑11.22) | 75.78 (↑32.11) |
| GPT-OSS | 20B | **79.12** | **75.52** | **68.59** | **76.12** | **80.90** (↑1.78) | **75.52** (↑0.00) | 70.51 (↑1.92) | **77.58** (↑1.46) |
| DeepSeek R1 | 7B | 41.28 | 40.34 | 65.06 | 46.23 | 66.79 (↑25.51) | 60.34 (↑19.99) | 63.78 (↓1.28) | 64.84 (↑18.61) |
| Mathstral | 7B | 21.23 | 27.93 | 53.85 | 29.62 | 40.33 (↑19.10) | 38.97 (↑11.04) | 64.42 (↑10.57) | 45.26 (↑15.64) |
| Gemini-2.5-Flash-Lite | N/A | 64.18 | 59.31 | 59.29 | 62.15 | 74.14 (↑9.96) | 71.38 (↑12.07) | 65.06 (↑5.77) | 71.63 (↑9.48) |

Table 9: Performance breakdown (Numerical, Symbolic, Proof, Overall) for Zero-Shot versus CoT on the MathMist BN-EN parallel corpus. The maximum values in each language and setting are highlighted as follows: Numerical, Symbolic, Proof, and Overall. Upward arrows, indicated by ↑, represent improvements, while downward arrows, shown as ↓, indicate a decrease in performance. Arrows in parentheses reflect changes relative to the Zero-Shot values.

and symbolic categories across most languages. It also exhibits competitive proof accuracy, leading in languages such as English, French, Kazakh, Finnish, Lithuanian, Turkish, Persian, and many low-resource languages. Gemini-2.5-Flash-Lite ranks as a solid second-tier model, achieving the next-best overall and proof accuracy averages. In some cases, it even surpasses GPT-OSS; for example, it demonstrates superior numerical performance in Bangla and better proof scores in Arabic, Gujarati, and Amharic. Qwen-8B and DeepSeek R1 7B are positioned in the middle tier. Both models show relatively strong proof capabilities in several languages. Notably, Qwen performs well in various European languages, while DeepSeek achieves the highest proof score for Bangla. However, both fall short compared to the top two models in terms of numerical and symbolic tasks. Mathstral 7B is the weakest model overall, particularly lacking in numerical and overall accuracy, with consistently lower scores across both high- and low-resource languages. In summary, GPT-OSS-20B excels in symbolic and numerical categories across languages. Gemini serves as a robust alternative with specific strengths in proof accuracy for certain languages. Qwen and DeepSeek are mid-tier models with selective strengths in proof, while Mathstral

| Models | #Param | Question Bangla |  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|---|---|---|
|  |  | CoT English |  |  |  | CoT Bangla |  |  |  |
|  |  | Numerical | Symbolic | Proof | Overall | Numerical | Symbolic | Proof | Overall |
| GPT-OSS | 20B | **79.48** | **70.00** | 67.95 | **75.09** | 76.51 (↓2.97) | 71.03 (↑1.03) | 66.67 (↓1.28) | 73.29 (↓1.80) |
| Qwen | 8B | 73.67 | 68.28 | **71.47** | 72.11 | 72.24 (↓1.43) | 70.69 (↑2.41) | 70.19 (↓1.28) | 71.49 (↓0.62) |
| DeepSeek R1 | 7B | 61.09 | 54.83 | 66.03 | 60.90 | 52.43 (↓8.66) | 53.45 (↓1.38) | 63.78 (↓2.25) | 55.09 (↓5.81) |
| Mathstral | 7B | 35.47 | 37.59 | 59.94 | 41.18 | 30.01 (↓5.46) | 30.34 (↓7.25) | 51.60 (↓8.34) | 34.74 (↓6.44) |
| **Models** | **#Param** | **Question English** |  |  |  |  |  |  |  |
|  |  | **CoT English** |  |  |  | **CoT Bangla** |  |  |  |
|  |  | Numerical | Symbolic | Proof | Overall | Numerical | Symbolic | Proof | Overall |
| GPT-OSS | 20B | **79.36** | **76.55** | **73.72** | **77.58** | 79.12 (↓0.24) | 75.52 (↓1.03) | 64.42 (↓9.30) | 75.22 (↓2.36) |
| Qwen | 8B | 78.05 | 72.76 | 72.44 | 75.78 | 76.75 (↓1.30) | 73.10 (↑0.34) | 66.99 (↓5.45) | 73.91 (↓1.87) |
| DeepSeek R1 | 7B | 66.79 | 60.34 | 63.78 | 64.84 | 58.60 (↓8.19) | 59.31 (↓1.03) | 62.50 (↓1.28) | 59.58 (↓5.26) |
| Mathstral | 7B | 40.33 | 38.97 | 64.42 | 45.26 | 32.86 (↓7.47) | 28.62 (↓10.35) | 55.13 (↓9.29) | 36.82 (↓8.44) |

Table 10: Accuracy breakdown (%) across mathematical problem types underneath English–Bangla code-switching reasoning. Each block contrasts aligned and cross-lingual settings across LLMs of different scales. Maximum scores are highlighted by category: Numerical, Symbolic, Proof, and Overall. Arrows (↑/↓) indicate performance change relative to the chain-of-thought (CoT) in English.

| Model | Metric | en | bn | fr | kk | fi | lt | tr | fa | ar | sw | ha | gu | am |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Qwen-8B | Overall | 43.67% | 55.36% | 52.11% | 47.4% | 50.73% | 45.4% | 49.62% | 68.1% | 32.73% | 24.98% | 23.39% | 40.76% | 23.39% |
| | Numerical | 37.49% | 54.92% | 47.45% | 43.18% | 45.2% | 38.2% | 44.6% | 67.14% | 24.56% | 18.86% | 18.27% | 32.15% | 19.69% |
| | Proof | 61.22% | 64.1% | 64.1% | 58.65% | 69.23% | 65.71% | 61.22% | 66.35% | 50.96% | 37.18% | 36.54% | 62.5% | 30.45% |
| | Symbolic | 42.76% | 47.24% | 52.76% | 47.59% | 46.9% | 44.48% | 51.72% | 72.76% | 36.9% | 29.66% | 24.14% | 42.41% | 26.55% |
| GPT-OSS-20B | Overall | 76.12% | 74.33% | 75.78% | 73.77% | 73.56% | 73.08% | 74.05% | 72.04% | 73.08% | 65.67% | 67.89% | 72.8% | 63.11% |
| | Numerical | 79.12% | 79.0% | 75.92% | 73.07% | 72.95% | 70.46% | 71.77% | 71.53% | 74.26% | 65.72% | 67.62% | 75.21% | 64.06% |
| | Proof | 68.59% | 62.5% | 75.0% | 76.28% | 74.04% | 77.56% | 77.56% | 71.15% | 66.67% | 66.35% | 68.27% | 65.38% | 58.65% |
| | Symbolic | 75.52% | 73.45% | 76.21% | 73.1% | 74.83% | 75.86% | 76.9% | 74.48% | 76.55% | 64.83% | 68.28% | 73.79% | 65.17% |
| DeepSeek R1 7B | Overall | 46.22% | 40.48% | 47.06% | 33.43% | 38.06% | 37.16% | 42.01% | 51.42% | 40.83% | 29.34% | 25.67% | 35.5% | 28.17% |
| | Numerical | 41.28% | 32.38% | 42.11% | 29.18% | 29.3% | 30.01% | 35.23% | 46.98% | 36.65% | 23.72% | 19.22% | 25.74% | 21.95% |
| | Proof | 65.06% | 67.31% | 65.38% | 42.31% | 59.62% | 58.01% | 61.54% | 62.5% | 52.88% | 43.27% | 41.03% | 59.29% | 41.99% |
| | Symbolic | 40.34% | 35.17% | 41.72% | 36.21% | 40.34% | 35.52% | 40.69% | 52.41% | 40.0% | 30.69% | 27.93% | 38.28% | 31.38% |
| Mathstral 7B | Overall | 29.63% | 31.43% | 31.28% | 19.24% | 17.92% | 22.91% | 23.04% | 25.54% | 22.77% | 15.09% | 8.86% | 21.66% | 11.21% |
| | Numerical | 21.23% | 24.08% | 21.71% | 11.27% | 9.96% | 14.47% | 13.05% | 16.61% | 14.95% | 10.32% | 5.1% | 13.4% | 7.71% |
| | Proof | 53.85% | 56.73% | 58.33% | 33.65% | 39.42% | 45.51% | 49.04% | 45.51% | 40.38% | 26.92% | 16.03% | 44.87% | 14.1% |
| | Symbolic | 27.93% | 25.52% | 30.0% | 26.9% | 17.93% | 23.1% | 24.14% | 30.0% | 26.55% | 16.21% | 12.07% | 20.69% | 18.28% |
| Gemini-2.5-Flash-Lite | Overall | 62.15% | 75.12% | 63.53% | 53.15% | 56.19% | 52.25% | 53.36% | 50.59% | 50.8% | 46.92% | 40.48% | 48.3% | 44.78% |
| | Numerical | 64.18% | 79.95% | 60.62% | 48.04% | 53.26% | 47.33% | 45.55% | 43.3% | 43.89% | 44.01% | 34.16% | 39.5% | 35.71% |
| | Proof | 59.29% | 65.06% | 68.27% | 61.54% | 61.22% | 66.99% | 69.87% | 68.27% | 68.91% | 55.45% | 54.17% | 69.55% | 65.38% |
| | Symbolic | 59.31% | 71.72% | 66.9% | 58.97% | 59.31% | 50.69% | 58.28% | 52.76% | 51.38% | 46.21% | 44.14% | 51.03% | 48.97% |

Table 11: Full Result by Category of MATHMIST. Here, en: English, bn: Bangla, fr: French, kk: Kazakh, fi: Finnish, lt: Lithuanian, tr: Turkish, fa: Persian, ar: Arabic, sw: Swahili, ha: Hausa, gu: Gujarati, am: Amharic.

underperforms compared to the other models. Moreover, the language composition tables (12) expose widespread code-switching reasoning during Bangla CoT: smaller models (DeepSeek R1, Mathstral) exhibit "Mixed" language outputs, injecting English, Cyrillic, etc. (Table 14).

| Language presence in CoT solutions — GPT-OSS-20B (Question: Bangla, CoT: Bangla) | | | | | |
|---|---|---|---|---|---|
| Aggregate language counts | | | Language combinations in CoT | | |
| Language | Count | Proportion (%) | Combination | Count | Proportion (%) |
| Bangla | 1188 | 82.2 | Bangla + English | 225 | 94.9 |
| English | 21 | 1.5 | Bangla + Chinese | 8 | 3.4 |
| Chinese | 0 | 0.0 | Bangla + Cyrillic + English | 1 | 0.4 |
| Mixed | 236 | 16.3 | Bangla + Chinese + English | 1 | 0.4 |
| | | | Bangla + English + Greek | 1 | 0.4 |

Table 12: Language composition in chain-of-thought (CoT) outputs generated by the GPT-OSS-20B model when prompted with Bangla questions and instructed to reason in Bangla. The table summarizes aggregate counts and proportions of detected languages, alongside mixed-language combinations observed in CoT reasoning traces. Notably, Mixed CoTs remain relatively limited, reflecting the model's strong linguistic alignment and controlled cross-lingual consistency.

| Language presence in CoT solutions — GPT-OSS-20B (Question: English, CoT: Bangla) | | | | | |
|---|---|---|---|---|---|
| Aggregate language counts | | | Language combinations in CoT | | |
| Language | Count | Proportion (%) | Combination | Count | Proportion (%) |
| Bangla | 1157 | 80.1 | Bangla + English | 267 | 99.3 |
| English | 19 | 1.3 | Bangla + Chinese + English | 1 | 0.4 |
| Chinese | 0 | 0.0 | Bangla + Chinese | 1 | 0.4 |
| Mixed | 269 | 18.6 | — | — | — |

Table 13: Aggregate language distribution in chain-of-thought (CoT) outputs for the GPT-OSS-20B model when prompted with English questions and instructed to reason in Bangla. The table summarizes the overall occurrence of individual languages and mixed-language combinations observed in CoT solutions. Here, Mixed indicates CoTs that contain linguistic tokens from multiple languages, revealing the extent of code-switching during multilingual reasoning.

**Language presence in CoT solutions — `DeepSeek R1-7B` (Question: Bangla, CoT: Bangla)**

| Aggregate language counts | | | Language combinations in CoT (percent of Mixed) | | |
|---|---|---|---|---|---|
| **Language** | **Count** | **Proportion (%)** | **Combination** | **Count** | **Proportion (%)** |
| Bangla | 523 | 36.2 | Bangla + English | 689 | 83.1 |
| English | 93 | 6.4 | Bangla + Cyrillic + English | 42 | 5.1 |
| Chinese | 0 | 0.0 | Bangla + Chinese + English | 39 | 4.7 |
| Mixed | 829 | 57.4 | Bangla + Chinese | 28 | 3.4 |
| | | | Bangla + English + Greek | 13 | 1.6 |
| | | | Arabic + Bangla + English | 8 | 1.0 |
| | | | Bangla + Chinese + Cyrillic + English | 3 | 0.4 |
| | | | Bangla + Chinese + Cyrillic | 2 | 0.2 |
| | | | Arabic + Bangla + Chinese + English + Japanese | 1 | 0.1 |
| | | | Arabic + Bangla + Chinese + English | 1 | 0.1 |
| | | | Arabic + Bangla + Cyrillic + English | 1 | 0.1 |
| | | | Arabic + Bangla + Chinese | 1 | 0.1 |
| | | | Arabic + Bangla + English + Greek | 1 | 0.1 |

Table 14: Aggregate distribution of languages in chain-of-thought (CoT) outputs for the `DeepSeek R1-7B` model when both the question and CoT were instructed in Bangla. The table summarizes the overall frequency and proportion of individual languages, as well as the composition and percentage of mixed-language CoTs. The majority of mixed outputs involve Bangla–English combinations, with occasional incorporation of additional scripts such as Cyrillic, Chinese, Arabic, Greek, and Japanese, reflecting the model's multilingual interference during reasoning.

**Language presence in CoT solutions — `DeepSeek-R1-7B` (Question: English, CoT: Bangla)**

| Aggregate language counts | | | Language combinations in CoT | | |
|---|---|---|---|---|---|
| **Language** | **Count** | **Proportion (%)** | **Combination** | **Count** | **Proportion (%)** |
| Bangla | 542 | 37.5 | Bangla + English | 611 | 78.7 |
| English | 126 | 8.7 | Bangla + Chinese + English | 62 | 8.0 |
| Chinese | 1 | 0.1 | Bangla + Cyrillic + English | 49 | 6.3 |
| Mixed | 776 | 53.7 | Bangla + Chinese | 10 | 1.3 |
| | | | Arabic + Bangla + English | 8 | 1.0 |
| | | | Bangla + English + Greek | 8 | 1.0 |
| | | | Bangla + Cyrillic | 4 | 0.5 |
| | | | Bangla + Chinese + Cyrillic | 4 | 0.5 |
| | | | Bangla + English + Korean | 3 | 0.4 |
| | | | Bangla + Chinese + Cyrillic + English | 3 | 0.4 |
| | | | Bangla + English + Japanese | 2 | 0.3 |
| | | | Bangla + English + Thai | 2 | 0.3 |
| | | | Bangla + Cyrillic + English + Greek | 2 | 0.3 |
| | | | Bangla + Chinese + English + Korean | 1 | 0.1 |
| | | | Arabic + Bangla + Chinese + English | 1 | 0.1 |
| | | | Bangla + Korean | 1 | 0.1 |
| | | | Arabic + Bangla + Cyrillic + English | 1 | 0.1 |
| | | | Arabic + Bangla | 1 | 0.1 |
| | | | Bangla + English + Greek + Thai | 1 | 0.1 |
| | | | Arabic + Bangla + English + Greek | 1 | 0.1 |
| | | | Bangla + Chinese + English + Japanese | 1 | 0.1 |

Table 15: Aggregate language distribution in chain-of-thought (CoT) outputs for the `DeepSeek-R1-7B` model when prompted with English questions and instructed to reason in Bangla. The table reports overall counts and proportions of languages present in the CoT, along with detailed statistics of mixed-language combinations. `Mixed` indicates CoTs containing multiple linguistic scripts or tokens from different languages, reflecting cross-lingual interference patterns.

| **Language presence in CoT solutions — `Qwen-3 8B` (Question: Bangla, CoT: Bangla)** | | | | | |
|---|---|---|---|---|---|
| **Aggregate language counts** | | | **Language combinations in CoT** | | |
| **Language** | **Count** | **Proportion (%)** | **Combination** | **Count** | **Proportion (%)** |
| Bangla | 1132 | 78.3 | Bangla + English | 190 | 88.4 |
| English | 116 | 8.0 | Bangla + English + Greek | 7 | 3.3 |
| Chinese | 0 | 0.0 | — | — | — |
| Mixed | 197 | 13.6 | — | — | — |

Table 16: Overall language distribution in chain-of-thought (CoT) outputs generated by the `Qwen-3 8B` model when prompted with Bangla questions and instructed to reason in Bangla. The table reports the proportions of individual languages detected in CoT solutions alongside the observed mixed-language combinations. `Mixed` indicates responses incorporating tokens from multiple languages.

| **Language presence in CoT solutions — `Qwen-3 8B` (Question: English, CoT: Bangla)** | | | | | |
|---|---|---|---|---|---|
| **Aggregate language counts** | | | **Language combinations in CoT** | | |
| **Language** | **Count** | **Proportion (%)** | **Combination** | **Count** | **Proportion (%)** |
| Bangla | 1111 | 76.9 | Bangla + English | 206 | 86.2 |
| English | 117 | 8.1 | Bangla + English + Greek | 10 | 4.2 |
| Chinese | 0 | 0.0 | Bangla + Chinese + English | 1 | 0.4 |
| Mixed | 217 | 15.0 | — | — | — |

Table 17: Aggregate language distribution in chain-of-thought (CoT) outputs for the `Qwen-3 8B` model when prompted with English questions and instructed to respond in Bangla. The table summarizes the overall presence and proportions of languages detected in CoT reasoning traces, alongside observed multilingual combinations. `Mixed` indicates CoTs containing tokens from multiple languages.

| **Language presence in CoT solutions — `Mathstral-7B` (Question: Bangla, CoT: Bangla)** | | | | | |
|---|---|---|---|---|---|
| **Aggregate language counts** | | | **Language combinations in CoT** | | |
| **Language** | **Count** | **Proportion (%)** | **Combination** | **Count** | **Proportion (%)** |
| Bangla | 610 | 42.1 | Bangla + English | 812 | 99.4 |
| English | 20 | 1.4 | Bangla + English + Greek | 3 | 0.4 |
| Chinese | 0 | 0.0 | | — | — |
| Mixed | 815 | 56.5 | — | — | — |

Table 18: Aggregate language distribution in chain-of-thought (CoT) outputs for the `Mathstral-7B` model when prompted with Bangla questions and instructed to respond in Bangla. The table reports overall counts and proportions of languages observed in CoT solutions, as well as the counts and percentages of mixed-language combinations. `Mixed` denotes CoTs containing tokens from more than one language.

| **Language presence in CoT solutions — `Mathstral-7B` (Question: English, CoT: Bangla)** | | | | | |
|---|---|---|---|---|---|
| **Aggregate language counts** | | | **Language combinations in CoT** | | |
| **Language** | **Count** | **Proportion (%)** | **Combination** | **Count** | **Proportion (%)** |
| Bangla | 598 | 41.4 | Bangla + English | 819 | 99.5 |
| English | 24 | 1.7 | Bangla + English + Greek | 2 | 0.2 |
| Chinese | 0 | 0.0 | Arabic + Bangla + English | 1 | 0.1 |
| Mixed | 823 | 57.0 | Bangla + Cyrillic + English | 1 | 0.1 |

Table 19: Aggregate language distribution in chain-of-thought (CoT) outputs for the `Mathstral-7B` model when prompted with English questions and instructed to respond in Bangla. The table reports overall counts and proportions of languages observed in CoT solutions, as well as the counts and percentages of mixed-language combinations. `Mixed` denotes CoTs containing tokens from more than one language.