

Multi-OphthaLingua: A Multilingual Benchmark for Assessing and Debiasing LLM Ophthalmological QA in LMICs

David Restrepo^{1*}, Chenwei Wu^{2*}, Zhengxu Tang², Zitao Shuai², Thao Nguyen Minh Phan⁴, Jun-En Ding⁷, Cong-Tinh Dao⁴, Jack Gallifant⁵, Robyn Gayle Dychiao⁶, Jose Carlo Artiaga⁶, André Hiroshi Bando³, Carolina Pelegrini Barbosa Gracitelli³, Vincenz Ferrer⁶, Leo Anthony Celi¹, Danielle Bitterman⁵, Michael G Morley⁵, Luis Filipe Nakayama¹

¹Massachusetts Institute of Technology, Cambridge, USA

²University of Michigan - Ann Arbor, Ann Arbor, USA

³Universidade Federal de São Paulo, São Paulo, Brazil

⁴National Yang Ming Chiao Tung University, Taipei, Taiwan

⁵Harvard University, Cambridge, USA

⁶University of the Philippines, Manila, Philippine

⁷Stevens Institute of Technology, Hoboken, USA

davidres@mit.edu

Abstract

Current ophthalmology clinical workflows are plagued by over-referrals, long waits, and complex and heterogeneous medical records. Large language models (LLMs) present a promising solution to automate various procedures such as triaging, preliminary tests like visual acuity assessment, and report summaries. However, LLMs have demonstrated significantly varied performance across different languages in natural language question-answering tasks, potentially exacerbating healthcare disparities in Low and Middle-Income Countries (LMICs). This study introduces the first multilingual ophthalmological question-answering benchmark with manually curated questions parallel across languages, allowing for direct cross-lingual comparisons. Our evaluation of 6 popular LLMs across 7 different languages reveals substantial bias across different languages, highlighting risks for clinical deployment of LLMs in LMICs. Existing debiasing methods such as Translation Chain-of-Thought or Retrieval-augmented generation (RAG) by themselves fall short of closing this performance gap, often failing to improve performance across all languages and lacking specificity for the medical domain. To address this issue, We propose CLARA (Cross-Lingual Reflective Agentic system), a novel inference time de-biasing method leveraging retrieval augmented generation and self-verification. Our approach not only improves performance across all languages but also significantly reduces the multilingual bias gap, facilitating equitable LLM application across the globe.

Introduction

Large Language Models (LLMs) such as Llama and GPT families have emerged as a transformative force in the field of artificial intelligence, offering new tools and solutions in healthcare, with ophthalmology presenting a particularly promising field for their applications (Rojas-Carabali et al.

2024). Characterized by high patient volumes and substantial documentation burdens (Nath et al. 2022; Lin et al. 2020), ophthalmology could benefit significantly from LLM integration, mainly in regions such as LMICs where specialized personnel are scarce resources (Malerbi and Andrade 2022). LLMs could potentially automate remote triage (Tan et al. 2020), clinical decision support (Nath et al. 2022), patient education (Yang et al. 2024b), and administrative workflows (Antaki et al. 2023).

While LLMs have shown remarkable potential in healthcare, their performance is not uniform across all languages (Marchisio et al. 2024; Plaza et al. 2024; Wang et al. 2024). These models typically perform best in English, benefiting from abundant training data, but often struggle with languages common in Low and Middle-Income Countries (LMICs) such as Portuguese, Spanish, Hindi, and Filipino (Marchisio et al. 2024; Zhao et al. 2024c; Dychiao et al. 2024), where the amount of ophthalmological data available is considerably limited (Restrepo et al. 2024a; Han et al. 2023). This disparity poses a significant challenge to the equitable deployment of LLMs in global healthcare (Lai, Mesgar, and Fraser 2024; Wang, Minervini, and Ponti 2024; Huang et al. 2023). Ironically, LMICs may stand to benefit the most from validated LLM applications like remote diagnostics (Henkel et al. 2023) in the future due to their limited trained personnel (Doshi et al. 2023; Restrepo et al. 2024b) compared to wealthier nations. Also, effective healthcare delivery in LMICs often requires communication in local languages (Mensah, Quao, and Group 2024). To fully realize the potential of LLMs in improving global health outcomes (Poulain, Fayyaz, and Beheshti 2024), it's crucial to evaluate and mitigate this linguistic bias (Wei et al. 2024) and ensure these advanced technologies can effectively serve diverse populations (Li et al. 2024c), regardless of their primary language (Kaur et al. 2024).

To better understand and address the linguistic disparities in LLM performance for ophthalmology, we present

*These authors contributed equally.

Copyright © 2025, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

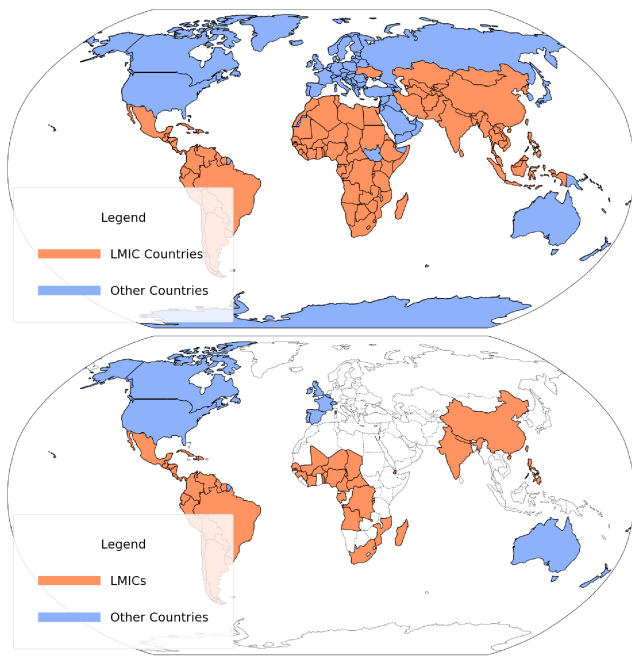


Figure 1: The upper map: Global distribution of Low and Middle-Income Countries (LMICs); The lower map: Countries and regions where the languages included in our benchmark are predominantly spoken (English, Portuguese, Spanish, Filipino, Mandarin, French and Hindi). Our dataset covers 49 LMIC countries and approximately 4.5 billion population.

Multi-OphthaLingua, the first multilingual ophthalmological QA dataset, comprised of 1184 questions across English, Spanish, Filipino, Portuguese, Mandarin, French, and Hindi. This dataset, created by ophthalmologists over the globe with diverse language backgrounds, covers a wide range of topics such as basic ophthalmology sciences, clinical cases, surgical practice and post-op care. The questions are structured as multiple-choice with four options each, carefully crafted to ensure question neutrality across regions. Board-certified native-speaker ophthalmologists reviewed each question-answer pair to guarantee robustness in assessing medical knowledge, language understanding, and cultural appropriateness. Most importantly, our dataset features paired questions across all languages, enabling direct cross-linguistic comparisons - a feature absent in most existing multilingual benchmarks, as shown in Table 1.

Our evaluation of 6 popular LLMs (Llama-2 70B, Llama-3 70B, Mixtral 8x7B, Qwen-2 72B, GPT 3.5, and GPT 4) reveals significant disparities in LLM performance across languages, with a notable gap for languages from LMICs such as Filipino. We observed that LLMs generally perform worse on clinical and surgical questions, indicating a lack of specialized domain knowledge. Our qualitative analyses show that these challenges arise from LLMs' limited abilities in LMIC languages, insufficient medical domain knowledge, and struggles with linguistic nuances. Existing work utilizes methods like English-based Chain of Thought

(EN-COT) and Pre-Translation (Ruder et al. 2021) to address language limitations, and Retrieval Augmented Generation (RAG) (Lewis et al. 2020) to compensate LLMs' lack of medical knowledge. However, these methods face challenges such as low availability of multilingual medical content and quality of matches, especially for LMIC languages. We address these issues by proposing a Cross-Lingual Reflective Agentic system (CLARA) specifically designed for multilingual debiasing in the medical context. CLARA employs a multi-agent approach, including translation, evaluation, knowledge augmentation, and rewriting agents. Extensive evaluation and ablation demonstrate that our approach simultaneously improves question-answering accuracy across all languages and reduces the cross-lingual performance gap.

The main contributions of this work are three-fold:

1. We introduce the first multilingual ophthalmology question-answering benchmark with paired data across seven languages, enabling direct cross-linguistic comparisons. A sample dataset and repo are publicly available at (<https://huggingface.co/datasets/AAAIBenchmark/Multi-Ophthalngua/tree/main>), and the full version will be released on Physionet, promoting reproducibility and future research in this field.
2. We provide both quantitative and qualitative investigation of the factors contributing to LLM failures in multilingual ophthalmology contexts, as well as why existing debiasing methods fall short. Our analysis offers valuable insights into the challenges of applying LLMs in diverse linguistic and medical settings.
3. We propose CLARA (Cross-Lingual Reflective Agentic system), a novel inference-time debiasing method specifically tailored for the medical domain. Through extensive evaluation, we demonstrate that CLARA significantly improves both overall accuracy and fairness across languages in ophthalmological question-answering tasks.

Related Work

Existing Work on LLM Multilingual Dataset and Biases in Medicine LLMs' unequal performance across languages in tasks such as question answering and numerical reasoning has raised concerns, as training corpora are primarily from resource-rich languages (Xu et al. 2024). Studies have revealed that LLMs in multilingual tasks suffer from language bias, demographic bias, and evaluation bias (Xu et al. 2024), significantly favoring Western continents in factual information and reasoning (Shafayat et al. 2024; Zhao et al. 2024b).

There is also a lack of comprehensive multilingual evaluation efforts for medical question-answering with LLMs, particularly in specialized domains like ophthalmology. As shown in Table 1, existing datasets are predominantly in English or Mandarin, with minimal representation of languages from LMICs. None of the existing datasets provide paired data across multiple languages, which is crucial for consistent evaluation of LLMs' multilingual capabilities. While some datasets are substantial in size (e.g., PubMedQA with 211k entries), they are limited to a single language and often focus on general medical knowledge rather than specialized

Dataset	Language	Paired Data	Size	Topic
MedQAUSMLE (Jin et al. 2021)	English	No	11.4k	medical exam QA dataset for disease diagnosis
PubMedQA (Jin et al. 2019)	English	No	211k	biomedical research questions QA dataset
MedMCQA (Pal, Umapathi, and Sankarasubbu 2022)	English	No	193k	MCQ dataset for medical entrance exams
MMLU-Medical (Hendrycks et al. 2021)	English	No	116	multitask medical MCQ
MedQA-MCML (Jin et al. 2021)	Mandarin	No	270k	QA dataset for solving medical problems
CMB-single (Wang et al. 2023)	Mandarin	No	34k	multi-level assessment for medical knowledge
CMMLU-Medical (Li et al. 2023a)	Mandarin	No	242	Chinese medical assessment suite QA dataset
CExam (Liu et al. 2023)	Mandarin	No	68k	Chinese medical licensing exam QA dataset
Headqa (Vilares and Gómez-Rodríguez 2019)	Spanish	No	7k	Spanish healthcare exam dataset
Frenchmedmcqa (Labrak et al. 2023)	French	No	3k	French medical exam MCQ dataset
MMLUHI (Chen et al. 2023)	Hindi	No	408	Hindi medical QA dataset for instruction fine-tuning
MMLUAra (Chen et al. 2023)	Arabic	No	401	Arabic medical QA dataset for instruction fine-tuning
Multi-OphthaLingua (ours)	English; Spanish; Mandarin; Portuguese; Filipino; Hindi; French	Yes	1184	Multilingual Benchmark for Assessing and Debiasing

Table 1: Comparisons between our proposed Multi-OphthaLingua and related medical QA benchmarks.

fields like ophthalmology. This gap underscores the need for a robust benchmark and holistic evaluation.

Existing LLM Debiasing Methods for Multilingual QA Recent efforts have introduced innovative methodologies to enhance the multilingual capabilities of LLMs, primarily in non-medical domains. Notable approaches include Cross-Lingual Template Prompting (XLT) (Huang et al. 2023; Li et al. 2023b), Pre-Translate COT (Intrator et al. 2024; Chai et al. 2024), and EN-COT (Ruder et al. 2021). XLT (Huang et al. 2023) employs a generic template prompt to engage LLMs’ cross-lingual and logical reasoning capabilities. While effective for simple questions, its applicability to complex medical queries may be limited. EN-COT (Ruder et al. 2021) generates a chain of thought directly in English, regardless of the original problem language, leveraging English for cross-lingual knowledge transfer. Pre-Translate COT (Intrator et al. 2024; Chai et al. 2024) involves translating problems into English before applying the English Chain of Thought (CoT) technique. However, it may not fully address the specific linguistic needs of clinicians due to inconsistent translation qualities. Frameworks like causality-guided debiasing (Li et al. 2024b) also provide a theoretical grounding for understanding and addressing biases in LLMs. Challenges persist in ensuring these techniques’ effectiveness across diverse medical terminologies and contexts.

Retrieval Augmented Generation and LLM Self-Verification While methods like EN-COT (Ruder et al. 2021) attempt to overcome language limitations, LLMs may still lack domain knowledge and not fully capture the nuances of medical terminology in different languages. Retrieval Augmented Generation (RAG) has emerged as a powerful technique to address LLMs’ lack of medical knowledge without requiring extra fine-tuning on the model (Ren et al. 2024; Grandinetti and McBeth 2024). However, RAG faces challenges in content relevance and quality of matches, especially for target LMIC languages with limited resources (Shi et al. 2024; Salemi and Zamani 2024). Self-verification techniques have shown potential in enhancing the reliability of AI-generated responses. Frameworks like Self-RAG (Self-Reflective Retrieval-Augmented Generation) (Asai et al. 2023) use retrieval and self-reflection mechanisms to cri-

tique and improve responses iteratively, enhancing the quality and factuality of generated text.

Benchmark Construction, Results and Analysis

This section details the processes of data collection, preparation, and technical implementation of our evaluation framework to assess LLM multilingual language understanding and medical knowledge. The proposed dataset aims to address the following key research questions (RQs):

RQ1: Are current LLMs equipped with domain knowledge to be useful for ophthalmologist assistance and safe for patients (e.g. understand clinical terms)?

RQ2: How and how much does LLM performance vary between languages from HICs and those from LMICs?

RQ3: What factors may contribute to any observed language disparities?

RQ4: Are current debiasing methods adequate to address language disparities?

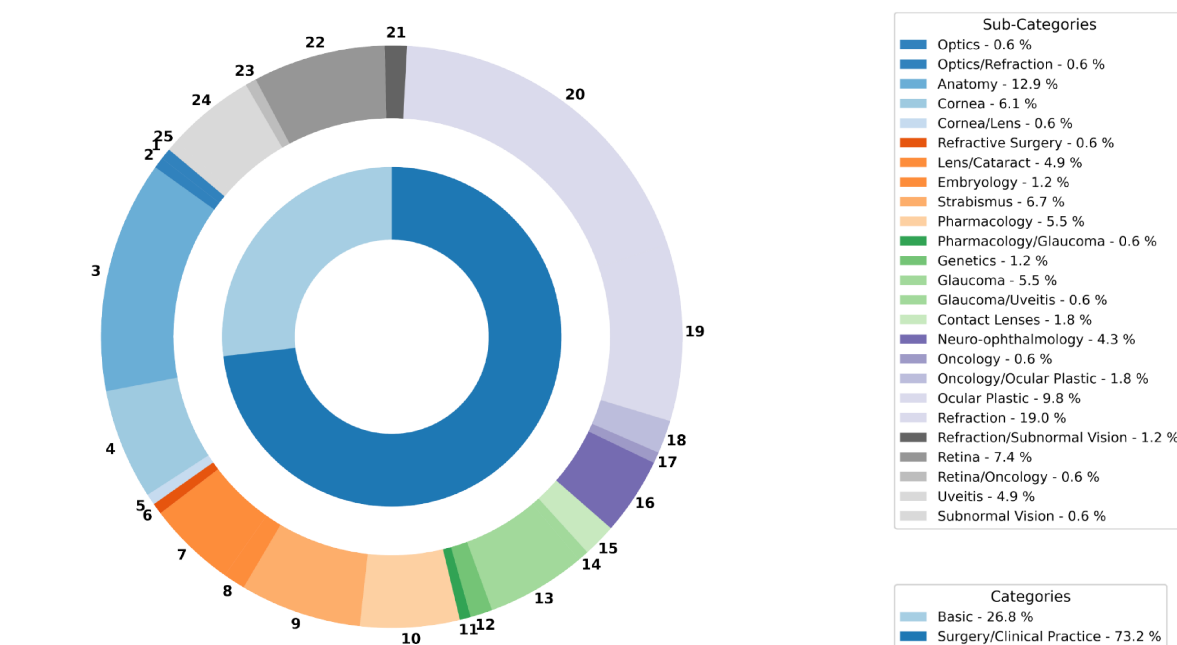
Benchmark Construction

To construct our dataset, 7 board-certified ophthalmologists with diverse language backgrounds over the globe curated a set of ophthalmological test questions, creating a multilingual dataset of 1184 questions.

The questions were manually designed and inspired by the Brazilian Ophthalmological Board exams, with clinical experts ensuring there would be neutrality in answers across different regions of the world. The benchmark consists of two high-level categories: basic sciences and clinical-surgical ophthalmology, with subgroups on anatomy, pharmacology, clinical optics, strabismus, cataract, uveitis, oncology, refractive surgery, contact lens, and genetics. The distribution of the questions is in Figure 2.

Originally written in Portuguese, these questions were manually translated into English, Spanish, Filipino, Mandarin, French, and Hindi to ensure broad linguistic, population, and geographical coverage. We select English as the most HIC-representative language, French, Spanish, and Portuguese as languages both spoken in HICs and LMICs, Chinese and Hindi as LMIC languages with large populations, and Filipino as LMIC languages with a small popu-

Distribution of Question Categories and Sub-Categories in the Benchmark



Portuguese Version

Q

Assinale a alternativa que melhor correlaciona as características histológicas com os respectivos tecidos oculares:

- 1.Monocamada de células fortemente unidas por complexos juncionais.
- 2.Estriações paralelas e regulares observadas à microscopia óptica, perpendiculares ao epitélio.
- 3.Contém células bipolares, células amácrinas, células horizontais e células de Muller.
- 4.Contém células magnocelulares, parvocelulares e coniocelulares.

A. Fotorreceptores.
B. Epitélio pigmentado da retina.
C. Camada ganglionar retiniana.
D. Camada nuclear interna.

A

B. Epitélio pigmentado da retina
C. Camada ganglionar retiniana

English Version

Q

Mark the alternative that best correlates the histological characteristics with the respective ocular tissues:

- 1.Monolayer of cells tightly joined together by junctional complexes.
- 2.Parallel and regular striations observed under optical microscopy, perpendicular to the epithelium.
- 3.It contains bipolar cells, amacrine cells, horizontal cells, and Muller cells.
- 4.It contains magnocellular, parvocellular, and coniocellular cells.

A. Photoreceptors.
B. Retinal pigmented epithelium.
C. Retinal ganglionic layer.
D. Inner nuclear layer.

A

B. Retinal pigmented epithelium
C. Retinal ganglionic layer

Figure 2: Left: An example question and answer in English and Portuguese; Right: Composition of the benchmark dataset by categories and subtypes.

lation. Each question-answer pair was reviewed and curated by board-certified native-speaker ophthalmologists to ensure a robust assessment of the models' medical knowledge, language correctness, and cultural appropriateness. A sample question in English and Portuguese is shown in Figure 2.

We evaluated our benchmark against 6 mainstream LLMs. The GPT 3.5 and GPT 4 models were implemented using the OpenAI API in Python 3.9.18, utilizing the OpenAI library version 1.40.3 for interacting with the language models. For the other models (LLAMA 2 70B, LLAMA 3 70B, Qwen-2 72B, and Mixtral 8x7B), Ollama and Together AI library was used. To facilitate a unified evaluation en-

vironment and enable advanced prompting techniques(Fan and Tao 2024), we employed the Langchain Python package for prompt template generation and API interaction across all models. We formulated standardized Chain-of-thought prompt templates for question-answering, aiming to eliminate any confounding variables related to differences in prompts or data leakage. The chain-of-thought process was stored for qualitative analysis, providing insights into the models' reasoning patterns. For quantitative evaluation, we implemented a JSON output schema of ABCD choices only and calculated the overall, subdomain-wise, and disease-wise accuracy. Each model's configuration was set to a con-

sistent number to reduce randomness (e.g. temperature = 0). The structure of the prompt is included in the Appendix.

Benchmark Results and LLM-Failure Analysis

The performance of LLMs differs significantly between languages from HICs and those from LMICs. As shown in Table 2, our quantitative evaluation results highlight significant disparities in the LLMs’ performance across languages, with the most notable underperformance in Filipino and Hindi. GPT-4 achieved only 51.8% accuracy in Filipino and 50.6% in Hindi, compared to 63.4% in English, a substantial 11.6% and 12.8 difference respectively. This gap is even more pronounced in Llama-3 70B with a difference of 14% in Filipino compared to English, and Mixtral, with a difference of 17.6% for Filipino, and 20.1% for Mandarin compared to English. As can be seen in table 1, the tendency of LMIC languages, such as Filipino (FIL), Hindi (HI) and Mandarin (ZH), consistently exhibit similar patterns of decreased accuracy across all models. One exception stands for Mandarin on Qwen-2, potentially due to the larger Mandarin corpus involved in its pretraining and its tokenizer being also trained on Chinese characters (Yang et al. 2024a).

LLMs are not equipped with sufficient ophthalmology domain-specific knowledge. We observed that more advanced LLMs demonstrate smaller performance gaps between languages. GPT-4, for instance, shows a narrower margin between its highest and lowest-performing languages compared to GPT-3.5. This trend is also evident in open-source models: Qwen-2 72B, which exhibits a smaller gap between English and Filipino performance compared to less sophisticated models like Llama-2 70B or Mixtral-8x7B. However, it is noteworthy that while these models show improvement in reducing language disparities, significant gaps persist. While the concrete composition of every model’s pretraining datasets is unknown, it is widely acknowledged that they are largely composed of more common languages, such as English, in online corpora. These findings pinpoint a concerning bias in these models, which tend to favor languages with extensive representation in their training datasets.

Performance degradation results from difficulties of LLMs in understanding clinic terms, linguistic nuances and cultural context. Our analysis also reveals a concerning trend of performance degradation when LLMs encounter more complex, clinically oriented questions. GPT-4’s average performance on clinical/surgical questions experiences a 3.79% drop from its basic science questions, while for Llama-3 and Qwen-2 this number goes up to 4.46% and 6.84%. This trend suggests a lack of specialized clinical knowledge in LLMs, which becomes more pronounced when prompting using LMIC languages.

Qualitative analysis by ophthalmologists of the CoT histories revealed striking examples of how LLMs struggle with the nuanced interpretation of medical terminology across different languages, potentially leading to critical misunderstandings in clinical contexts. Our complete qualitative analysis is included in the Appendix. For instance, when presented with the Filipino term “namamaga,” which can mean both “swollen” and “inflamed”, GPT-3.5 consistently inter-

preted it as “swollen” in all contexts, missing the subtle distinction that could be crucial in diagnosing conditions like uveitis. Similarly, in Portuguese, the term “mancha” can refer to both a “spot” and a “stain,” leading to ambiguous interpretations in descriptions of retinal abnormalities.

We observed that cultural context significantly influenced the models’ responses, particularly in post-operative-related queries. When asked about post-operative care in Spanish, GPT-4 emphasized the role of family support, reflecting cultural norms in many Spanish-speaking countries. However, this emphasis was notably absent in English responses, which focused more on clinical follow-up procedures. This discrepancy highlights the models’ inconsistent incorporation of cultural nuances in medicine across languages. In Filipino CoT histories, we noticed a tendency for all models to use more colloquial language when discussing symptoms, often employing idiomatic expressions that lacked the precision required in medical communication. For example, it used “parang may lumutang na langaw” (like there’s a floating fly) to describe a visual disturbance, an expression that doesn’t directly translate to the medical term “floaters” used in English.

These qualitative observations highlight not just linguistic barriers but also the need for models to understand and appropriately navigate cultural contexts, idiomatic expressions, and region-specific health concerns across different languages. Such nuanced understanding is needed for the responsible and effective deployment of AI in global healthcare settings.

	EN	ES	PT	FIL	ZH	HI	FR
GPT 4	63.4	65.2	61.6	51.8	52.4	50.6	62.8
GPT 3.5	46.2	38.4	39	34.8	32.3	37.2	38.4
Llama-3 70B	57.3	51.8	53.7	43.3	46.3	44.5	53
Llama-2 70B	33.5	32.9	29.9	26.2	29.9	29.3	33.5
Mixtral-8x7B	52.4	47	47	34.8	32.3	42.1	48.2
Qwen-2 72B	58.5	56.7	55.5	49.4	55.5	48.8	59.1
GPT 4 Basic	65.9	70.5	65.9	45.5	59.1	56.8	63.6
GPT 3.5 Basic	47.5	39.2	41.2	38.3	38.6	38.6	40.9
Llama-3 70B Basic	56.8	50	61.4	43.2	54.5	45.5	61.4
Llama-2 70B Basic	36.4	29.5	25	25	31.8	22.7	34.1
Mixtral-8x7B Basic	52.3	40.9	50	27.3	50	40.9	52.3
Qwen-2 72B Basic	63.6	59.1	59.1	50	63.6	54.5	63.6
GPT 4 Surgery	62.5	63.3	60	54.2	50	48.3	62.5
GPT 3.5 Surgery	45.7	38.1	38.2	33.5	30	36.7	37.5
Llama-3 70B Surgery	57.5	52.5	50.8	43.3	43.3	44.2	50
Llama-2 70B Surgery	32.5	34.2	31.7	26.7	29.2	31.7	33.3
Mixtral-8x7B Surgery	52.5	49.2	45.8	37.5	25.8	42.5	46.7
Qwen-2 72B Surgery	53.7	51.8	54.2	49.2	52.5	46.7	57.5

Table 2: Performance Across Different LLMs, Languages and Subgroups, EN-English, ES-Spanish, PT-Portuguese, FIL-Filipino/Tagalog, ZH-Mandarin Chinese, HI-Hindi, FR-French. Results averaged by 8 runs.

Debiasing LLMs for Multilingual Ophthalmology QA

Our evaluation of LLMs in multilingual ophthalmology question-answering reveals several existing challenges. Primarily, LLMs exhibit a lack of language proficiency in LMIC languages, compounded by insufficient medical domain knowledge. This knowledge gap often causes mod-

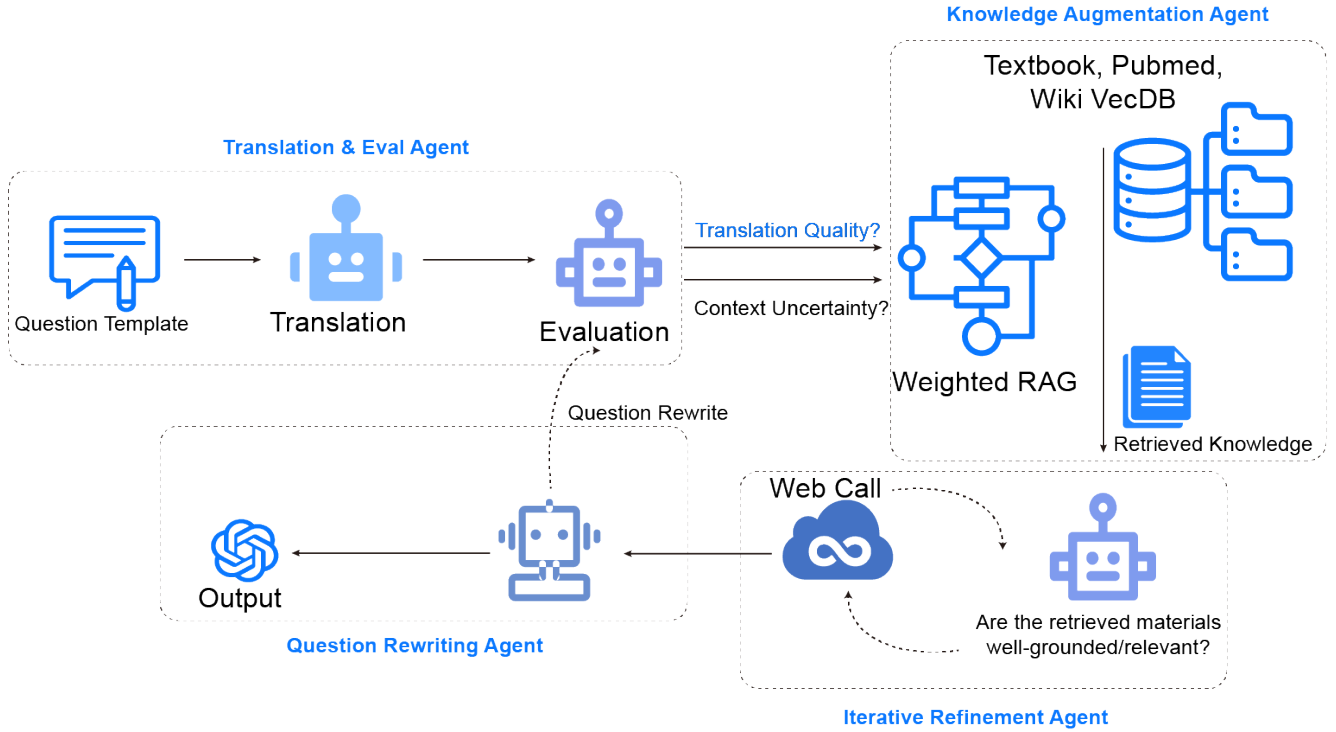


Figure 3: Illustration of CLARA workflow

		EN	ES	PT	FIL	ZH	HIN	FR
GPT-4	Direct Inference	63.4	65.2	61.6	51.8	52.4	50.6	62.8
	Gap	0	1.8	-1.8	-11.6	-11	-12.8	-0.6
	Web-ToolCall	68.9	65.2	65.9	56.8	54.3	59.8	64.0
	Gap	0	-3.7	-3	-12.1	-14.6	-9.1	-4.9
	Translate-COT	69.5	67	68.2	61.6	66.2	65.3	66.7
	Gap	0	-2.5	-1.3	-7.9	-3.3	-4.2	-2.8
GPT-3.5	CLARA(Ours)	72.2	70.7	71.8	67.1	70.2	68.4	69.8
	Gap	0	-1.5	-0.4	-5.1	-2	-3.8	-2.4
	Direct Inference	46.2	38.4	39	34.8	32.3	37.2	38.4
	Gap	0	-7.8	-7.2	-11.4	-13.9	-9	-7.8
	Web-ToolCall	41.5	41.5	42.1	35.4	31.1	37.2	37.8
	Gap	0	0	0.6	-6.1	-10.4	-4.3	-3.7
	Translate-COT	48.6	42.7	42.1	40.8	42.5	42.3	43.7
	Gap	0	-5.9	-6.5	-7.8	-6.1	-6.3	-4.9
	Ours	53.6	48.7	48.8	45.7	48.3	47.8	49.1
	Gap	0	-4.9	-4.8	-7.9	-5.3	-5.8	-4.5

Table 3: Debias Results of GPT-3.5 and GPT-4

els to generate plausible but incorrect reasoning. Another contributor to LLM’s poor performance is that LLMs often struggle with understanding nuanced linguistic differences across languages, which can lead to misinterpretations in medical contexts (Zhu et al. 2024).

Baselines

Several baseline approaches have been proposed to address these challenges, each with its own limitations. To tackle language differences, methods such as direct inference and pre-translation have been explored. Direct inference attempts to prompt the LLM to process and respond in the target language directly, but this approach may be ineffective for complex medical queries in diverse languages where

the model’s proficiency is limited. Pre-translation, which involves translating the input to a high-resource language (typically English) and then performing the inference, raises concerns about the accuracy and fidelity of translations, particularly for medical terminology and nuanced symptom descriptions (Chai et al. 2024; Intrator et al. 2024). Addressing the lack of medical knowledge, some researchers have proposed Web Search Augmentation, utilizing web-search APIs (Tao, Fan, and Yang 2024) to ground the LLM’s reasoning with a more reliable and traceable knowledge base at inference time (Vu et al. 2023). However, this method relies heavily on the quality of the knowledge base and the quality of retrieval. Otherwise, this approach risks introducing noisy and incorrect or irrelevant information, potentially leading the LLM to diverge with non-medical or unreliable content. Another approach, RAG, involves retrieving relevant information from curated databases like PubMed or medical textbooks (Li et al. 2024a). While promising, RAG faces challenges in the scarcity of high-quality retrieval materials in target LMIC languages, and ensuring the relevance and accuracy of retrieved information remains an active area of research (Doshi et al. 2023).

CLARA: Cross-Lingual Reflective Agent

Inspired by the qualitative and quantitative findings, we propose CLARA (Cross-Lingual Reflective Agentic system), a novel method to address bias in multilingual ophthalmology question-answering. CLARA combines pre-translation, evaluation, corrective RAG, web search, and query transformation within an agentic framework to enhance the robust-

ness and accuracy of responses across diverse languages. Inspired by the concept of agentic AI (Talebirad and Nadiri 2023; Zhao et al. 2024a), CLARA employs multiple specialized agents that collaborate to process and respond to complex queries. Figure 3 illustrates our pipeline.

Translation and Initial Evaluation Agent The process begins with the Translation Agent converting the input query to English, standardizing inputs across languages. An Evaluation Agent, functioning as a meta-cognitive component, then performs a dual assessment: first, it evaluates the translation quality and certainty; second, it gauges the LLM’s overall certainty about the medical question, identifying potential issues with jargon or contextual understanding. This comprehensive evaluation determines the subsequent actions in the pipeline.

Knowledge Augmentation Agent Based on the Evaluation Agent’s assessment, CLARA’s Knowledge Agent triggers one of the two following RAG approaches. This involves querying a vector embedding database, with weights assigned based on the uncertainty level of different query parts. For parts of the query where translation uncertainty is expressed, a weighted RAG approach is used. We add an additional relevance score to the full-original-query score, here the add-on relevance score R_i for each retrieved document i is calculated as:

$$R_i = \sum (w_j * \text{sim}(q_j, d_i)) \quad (1)$$

where w_j is the weight of query part j , and $\text{sim}(q_j, d_i)$ is the cosine similarity between query part j and document i .

For parts requiring additional context or containing domain-specific jargon, a reweighted RAG approach is applied as well. We perform jargon handling by our Knowledge Augmentation agent, where domain-specific terms are identified and expanded using a specialized ophthalmology dictionary. Key ophthalmological concepts are enriched with relevant contextual information and formatted next to the concept in the prompt. The reweighted relevance score RR_i for each document i is then calculated as:

$$RR_i = \sum (w_j * \text{sim}(q_j, d_i)) + \sum (w_k * \text{sim}(j_k, d_i)) \quad (2)$$

where w_k is the weight assigned to jargon term k , and j_k is the expanded definition or context for that term.

We curated a diverse set of RAG corpora from three distinct sources, each contributing unique aspects of medical and general knowledge. PubMed provides a comprehensive repository of biomedical abstracts, widely recognized in the field (Canese and Weis 2013). To ensure in-depth, domain-specific knowledge, we incorporated medical textbooks. Additionally, we included Wikipedia to cover general knowledge aspects to broaden the width of our knowledge base (Vrandečić and Krötzsch 2014). Full details of our RAG sources can be found in Table 4. We use MedCPT-Query-Encoder (Jin et al. 2023) as our RAG retriever in our model, which is specifically designed for medical domain queries and helps ensure more accurate and relevant retrievals for ophthalmological content.

Corpus	#Doc.	#Snippets	Length
PubMed	320k	2.8M	200
Textbooks	15	106.8k	200
Wikipedia	2M	14.7M	200

Table 4: RAG Corpus Overview

Iterative Evaluation (of Retrieval) and Refinement Agent

CLARA employs an iterative evaluation process where a second Evaluation Agent, acting as a critic, assesses the relevance and utility of the retrieved documents. This agent determines whether the retrieved and augmented information is useful for answering the query. If the information is deemed insufficient or irrelevant, it is discarded, and the system’s Web Search Tool (using Tavily API) initiates a search for additional information. This iterative process continues until the Evaluation Agent determines that sufficient relevant information has been gathered or a maximum iteration limit = 5 is reached. Then all collected information along with the translated question is passed for final question answering.

Question Rewriting Agent When the maximum rounds are reached, and RAG and web searches fail to yield useful information, CLARA triggers its Rewriting Agent. This situation often arises due to complex, nested information in ophthalmological queries. For instance, consider an ophthalmological examination case that states: “Bilateral papilledema noted, more pronounced in the right eye with flame-shaped hemorrhages, the left eye showing early cotton wool spots and an area of possible choroidal neovascularization temporal to the macula.” Here, the right eye’s information is omitted and may cause confusion. Our Rewriting Agent recomposes the translated question and passes the rewritten question back to the first evaluation agent, addressing the limitation in complex information extraction from the query. This structured rewriting helps the LLM to process intricate ophthalmological queries and allows for more targeted information retrieval in subsequent RAG iterations.

Through this multi-agent, reflective process, CLARA aims to mitigate biases and enhance accuracy in multilingual ophthalmology QA, addressing the challenges of language diversity and domain-specific knowledge in medical AI.

Debias Results Analysis and Ablation Studies

1	2	3	4	5	EN	ES	PT	FIL	ZH	HIN	FR
N	N	N	N	N	66.4	63.2	63.4	51.8	52.4	50.6	62.8
Y	N	N	N	N	69.5	67.0	68.2	61.6	66.2	65.3	66.7
Y	Y	N	N	N	69.6	67.5	68.4	61.8	66.4	65.5	67.1
Y	Y	Y	N	N	70.1	68.9	69.3	62.5	68.2	67.4	68.7
Y	Y	Y	Y	N	70.8	69.4	69.7	64.9	69.3	67.9	69.5
Y	Y	Y	Y	Y	72.2	70.7	71.8	67.1	70.2	68.4	69.8

Table 5: Ablation Study for GPT-4, 1:Translate-COT, 2:Web ToolCall, 3:Basic-RAG, 4:Corrective-RAG, 5:CLARA

Current de-bias methods are not sufficient to address the performance disparity between HICs and LMICs lan-

guages. The results in Table 3 demonstrate the varied effectiveness of debiasing techniques for multilingual ophthalmology question-answering using GPT-3.5 and GPT-4, revealing important insights when analyzing both performance gaps (relative to English) and absolute accuracy. Direct Inference, the baseline approach, exhibits the largest performance gaps between English and LMIC languages, particularly for Filipino (11.6% for GPT-4, 11.4% for GPT-3.5), Mandarin (11.0% for GPT-4, 13.9% for GPT-3.5), and Hindi (12.8% for GPT-4, 9.0% for GPT-3.5). This method's overall accuracy is also the lowest across languages, leaving lower-resource languages at a significant disadvantage.

Web-ToolCall demonstrates inconsistent results, both in terms of fairness gap reduction and absolute performance. For GPT-3.5, it hurts the performance of French and Mandarin by 0.6% and 1.2% and offers no value for Hindi. For GPT-4, while it improves absolute performance for most languages, we observe a concerning larger performance gap for Spanish, Portuguese, and French. This inconsistency highlights the unreliability of Web-ToolCall, suggesting that web search processes reliant on scarce LMIC medical text may introduce noisy information, particularly for non-English queries. Translate-COT (Shi et al. 2022; Ruder et al. 2021) shows more consistent improvements in both gap reduction and absolute performance across languages for both models. Notably, for GPT-4, it helps Mandarin, Hindi and Filipino pass the benchmark (60%). However, it still falls short of achieving parity for Hindi and Filipino, especially for less advanced LLMs like GPT-3.5.

Our proposed method demonstrates superior performance in both aspects. It consistently reduces performance gaps across all languages while simultaneously improving absolute accuracy, even for English. Compared to Translate-COT, our method not only narrows the Filipino-English gap from 7.9% to 5.1% but also boosts Filipino performance from 61.6% to 67.1%. Similar improvements are seen in Mandarin and Hindi.

The ablation study for GPT-4 reveals the incremental benefits of each component in CLARA. Details of how each component is implemented is included in Appendix. Translation alone yields substantial improvements, particularly for lower-resource languages, with Filipino, Mandarin, and Hindi seeing increases of 9.8%, 13.8%, and 14.7%, respectively. Web search capabilities add modest but consistent gains across languages when coupled with Translation, indicating that English-based web retrieval is more reliable than LMIC language-based. Basic RAG further enhances performance, with Filipino, Chinese, and Hindi improving by an additional 0.7%, 1.8%, and 1.9%. The corrective-RAG component shows language-dependent improvements, most notably for Filipino (+2.4%). The full CLARA system achieves the best results, with Filipino, Mandarin, and Hindi reaching 67.1%, 70.2%, and 68.4%. Importantly, CLARA also improves English performance from 66.4% to 72.2%, indicating enhanced overall model capability.

Conclusion and Broader Impacts

Our work contributes to more equitable access to medical information across diverse linguistic communities, potentially

enhancing healthcare delivery in resource-limited settings. While our method improves performance across languages, the persistent limitations in less advanced models like GPT-3.5 raise ethical concerns about deploying medical AI systems in the real world. This underscores the need for continued research and careful consideration of AI's role in healthcare.

References

- Antaki, F.; Touma, S.; Milad, D.; El-Khoury, J.; and Duval, R. 2023. Evaluating the performance of ChatGPT in ophthalmology: an analysis of its successes and shortcomings. *Ophthalmology science*, 3(4): 100324.
- Asai, A.; Wu, Z.; Wang, Y.; Sil, A.; and Hajishirzi, H. 2023. Self-rag: Learning to retrieve, generate, and critique through self-reflection. *arXiv preprint arXiv:2310.11511*.
- Canese, K.; and Weis, S. 2013. PubMed: the bibliographic database. *The NCBI handbook*, 2(1).
- Chai, L.; Yang, J.; Sun, T.; Guo, H.; Liu, J.; Wang, B.; Liang, X.; Bai, J.; Li, T.; Peng, Q.; et al. 2024. xcot: Cross-lingual instruction tuning for cross-lingual chain-of-thought reasoning. *arXiv preprint arXiv:2401.07037*.
- Chen, Z.; Yan, S.; Liang, J.; Jiang, F.; Wu, X.; Yu, F.; Chen, G. H.; Chen, J.; Zhang, H.; Jianquan, L.; Xiang, W.; and Wang, B. 2023. MultilingualSIFT: Multilingual Supervised Instruction Fine-tuning.
- Doshi, J.; Kashyap Jois, A. K.; Hanna, K.; and Anandan, P. 2023. The LLM Landscape for LMICs. *arxiv*.
- Dychiao, R. G. K.; Alberto, I. R. I.; Artiaga, J. C. M.; Salongcay, R. P.; and Celi, L. A. 2024. Large language model integration in Philippine ophthalmology: early challenges and steps forward. *The Lancet Digital Health*, 6(5): e308.
- Fan, X.; and Tao, C. 2024. Towards resilient and efficient llms: A comparative study of efficiency, performance, and adversarial robustness. *arXiv preprint arXiv:2408.04585*.
- Grandinetti, J.; and McBeth, R. 2024. From Generalist to Specialist: Improving Large Language Models for Medical Physics Using ARCoT. *arXiv preprint arXiv:2405.11040*.
- Han, X.; Zhang, J.; Liu, Z.; Tan, X.; Jin, G.; He, M.; Luo, L.; and Liu, Y. 2023. Real-world visual outcomes of cataract surgery based on population-based studies: a systematic review. *British Journal of Ophthalmology*, 107(8): 1056–1065.
- Hendrycks, D.; Burns, C.; Basart, S.; Zou, A.; Mazeika, M.; Song, D.; and Steinhardt, J. 2021. Measuring Massive Multitask Language Understanding. *Proceedings of the International Conference on Learning Representations (ICLR)*.
- Henkel, O.; Hills, L.; Roberts, B.; and McGrane, J. 2023. Can LLMs Grade Short-answer Reading Comprehension Questions: Foundational Literacy Assessment in LMICs. *arXiv preprint arXiv:2310.18373*.
- Huang, H.; Tang, T.; Zhang, D.; Zhao, W. X.; Song, T.; Xia, Y.; and Wei, F. 2023. Not All Languages Are Created Equal in LLMs: Improving Multilingual Capability by Cross-Lingual-Thought Prompting. *arXiv preprint arXiv:2305.07004*.

- Intrator, Y.; Halfon, M.; Goldenberg, R.; Tsarfaty, R.; Eyal, M.; Rivlin, E.; Matias, Y.; and Aizenberg, N. 2024. Breaking the Language Barrier: Can Direct Inference Outperform Pre-Translation in Multilingual LLM Applications? *arXiv preprint arXiv:2403.04792*.
- Jin, D.; Pan, E.; Oufattole, N.; Weng, W.-H.; Fang, H.; and Szolovits, P. 2021. What disease does this patient have? a large-scale open domain question answering dataset from medical exams. *Applied Sciences*, 11(14): 6421.
- Jin, Q.; Dhingra, B.; Liu, Z.; Cohen, W.; and Lu, X. 2019. PubMedQA: A Dataset for Biomedical Research Question Answering. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, 2567–2577.
- Jin, Q.; Kim, W.; Chen, Q.; Comeau, D. C.; Yeganova, L.; Wilbur, W. J.; and Lu, Z. 2023. MedCPT: Contrastive Pre-trained Transformers with large-scale PubMed search logs for zero-shot biomedical information retrieval. *Bioinformatics*, 39(11): btad651.
- Kaur, D.; Uslu, S.; Durresi, M.; and Durresi, A. 2024. LLM-Based Agents Utilized in a Trustworthy Artificial Conscience Model for Controlling AI in Medical Applications. In *International Conference on Advanced Information Networking and Applications*, 198–209. Springer.
- Labrak, Y.; Bazoge, A.; Dufour, R.; Rouvier, M.; Morin, E.; Daille, B.; and Gourraud, P.-A. 2023. FrenchMedMCQA: A French multiple-choice question answering dataset for medical domain. *arXiv preprint arXiv:2304.04280*.
- Lai, W.; Mesgar, M.; and Fraser, A. 2024. LLMs Beyond English: Scaling the Multilingual Capability of LLMs with Cross-Lingual Feedback. *arXiv preprint arXiv:2406.01771*.
- Lewis, P.; Perez, E.; Piktus, A.; Petroni, F.; Karpukhin, V.; Goyal, N.; Küttler, H.; Lewis, M.; Yih, W.-t.; Rocktäschel, T.; et al. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33: 9459–9474.
- Li, D.; Kadav, A.; Gao, A.; Li, R.; and Bourgon, R. 2024a. Automated Clinical Data Extraction with Knowledge Conditioned LLMs. *arXiv preprint arXiv:2406.18027*.
- Li, H.; Zhang, Y.; Koto, F.; Yang, Y.; Zhao, H.; Gong, Y.; Duan, N.; and Baldwin, T. 2023a. CMMLU: Measuring massive multitask language understanding in Chinese. *arXiv:2306.09212*.
- Li, J.; Tang, Z.; Liu, X.; Spirtes, P.; Zhang, K.; Leqi, L.; and Liu, Y. 2024b. Steering LLMs Towards Unbiased Responses: A Causality-Guided Debiasing Framework. *arXiv preprint arXiv:2403.08743*.
- Li, J.; Zhang, H.; Zhang, F.; Chang, T.-W.; Kuang, K.; Chen, L.; and Zhou, J. 2024c. Optimizing Language Models with Fair and Stable Reward Composition in Reinforcement Learning. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, 10122–10140.
- Li, S.; Hu, X.; Liu, A.; Yang, Y.; Ma, F.; Yu, P. S.; and Wen, L. 2023b. Enhancing cross-lingual natural language inference by soft prompting with multilingual verbalizer. *arXiv preprint arXiv:2305.12761*.
- Lin, W.-C.; Chen, J. S.; Chiang, M. F.; and Hribar, M. R. 2020. Applications of artificial intelligence to electronic health record data in ophthalmology. *Translational vision science & technology*, 9(2): 13–13.
- Liu, J.; Zhou, P.; Hua, Y.; Chong, D.; Tian, Z.; Liu, A.; Wang, H.; You, C.; Guo, Z.; Zhu, L.; et al. 2023. Benchmarking Large Language Models on CMExam—A Comprehensive Chinese Medical Exam Dataset. *arXiv preprint arXiv:2306.03030*.
- Malerbi, F. K.; and Andrade, R. E. 2022. Real-World diabetic retinopathy screening with a handheld fundus camera in a high-burden setting. *Acta Ophthalmologica (1755375X)*, 100(8).
- Marchisio, K.; Ko, W.-Y.; Bérard, A.; Dehaze, T.; and Ruder, S. 2024. Understanding and Mitigating Language Confusion in LLMs. *arXiv preprint arXiv:2406.20052*.
- Mensah, P. B.; Quao, N. S.; and Group, P. G. C. E. 2024. Can Large Language Models Provide Emergency Medical Help Where There Is No Ambulance? A Comparative Study on Large Language Model Understanding of Emergency Medical Scenarios in Resource-Constrained Settings. *medRxiv*, 2024–04.
- Nath, S.; Marie, A.; Ellershaw, S.; Korot, E.; and Keane, P. A. 2022. New meaning for NLP: the trials and tribulations of natural language processing with GPT-3 in ophthalmology. *British Journal of Ophthalmology*, 106(7): 889–892.
- Pal, A.; Umapathi, L. K.; and Sankarasubbu, M. 2022. Medmcqa: A large-scale multi-subject multi-choice dataset for medical domain question answering. In *Conference on health, inference, and learning*, 248–260. PMLR.
- Plaza, I.; Melero, N.; del Pozo, C.; Conde, J.; Reviriego, P.; Mayor-Rocher, M.; and Grandury, M. 2024. Spanish and LLM Benchmarks: is MMLU Lost in Translation? *arXiv preprint arXiv:2406.17789*.
- Poulain, R.; Fayyaz, H.; and Beheshti, R. 2024. Bias patterns in the application of LLMs for clinical decision support: A comprehensive study. *arXiv preprint arXiv:2404.15149*.
- Ren, Z.; Zhan, Y.; Yu, B.; Ding, L.; and Tao, D. 2024. Healthcare copilot: Eliciting the power of general llms for medical consultation. *arXiv preprint arXiv:2402.13408*.
- Restrepo, D.; Quion, J. M.; Do Carmo Novaes, F.; Azevedo Costa, I. D.; Vasquez, C.; Bautista, A. N.; Quiminiano, E.; Lim, P. A.; Mwavu, R.; Celi, L. A.; et al. 2024a. Ophthalmology Optical Coherence Tomography Databases for Artificial Intelligence Algorithm: A Review. In *Seminars in Ophthalmology*, volume 39, 193–200. Taylor & Francis.
- Restrepo, D.; Wu, C.; Vásquez-Venegas, C.; Matos, J.; Galifant, J.; and Nakayama, L. F. 2024b. Analyzing Diversity in Healthcare LLM Research: A Scientometric Perspective. *medRxiv*, 2024–06.
- Rojas-Carabali, W.; Agrawal, R.; Gutierrez-Sinisterra, L.; Baxter, S. L.; Cifuentes-González, C.; Wei, Y. C.; Arputhan, A. J.; Kannapiran, P.; Wong, S.; Lee, B.; et al. 2024. Natural Language Processing in Medicine and Ophthalmology:

- A Review for the 21st-century clinician. *Asia-Pacific Journal of Ophthalmology*, 100084.
- Ruder, S.; Constant, N.; Botha, J.; Siddhant, A.; Firat, O.; Fu, J.; Liu, P.; Hu, J.; Garrette, D.; Neubig, G.; et al. 2021. XTREME-R: Towards more challenging and nuanced multilingual evaluation. *arXiv preprint arXiv:2104.07412*.
- Salemi, A.; and Zamani, H. 2024. Evaluating Retrieval Quality in Retrieval-Augmented Generation. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval*, 2395–2400.
- Shafayat, S.; Kim, E.; Oh, J.; and Oh, A. 2024. Multi-FAct: Assessing Multilingual LLMs’ Multi-Regional Knowledge using FActScore. *arXiv preprint arXiv:2402.18045*.
- Shi, F.; Suzgun, M.; Freitag, M.; Wang, X.; Srivats, S.; Vosoughi, S.; Chung, H. W.; Tay, Y.; Ruder, S.; Zhou, D.; et al. 2022. Language models are multilingual chain-of-thought reasoners. *arXiv preprint arXiv:2210.03057*.
- Shi, Y.; Zi, X.; Shi, Z.; Zhang, H.; Wu, Q.; and Xu, M. 2024. Enhancing Retrieval and Managing Retrieval: A Four-Module Synergy for Improved Quality and Efficiency in RAG Systems. *arXiv preprint arXiv:2407.10670*.
- Talebirad, Y.; and Nadiri, A. 2023. Multi-agent collaboration: Harnessing the power of intelligent llm agents. *arXiv preprint arXiv:2306.03314*.
- Tan, Y.; Bacchi, S.; Casson, R. J.; Selva, D.; and Chan, W. 2020. Triaging ophthalmology outpatient referrals with machine learning: a pilot study. *Clinical & experimental ophthalmology*, 48(2): 169–173.
- Tao, C.; Fan, X.; and Yang, Y. 2024. Harnessing llms for api interactions: A framework for classification and synthetic data generation. *arXiv preprint arXiv:2409.11703*.
- Vilares, D.; and Gómez-Rodríguez, C. 2019. HEAD-QA: A Healthcare Dataset for Complex Reasoning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 960–966. Florence, Italy: Association for Computational Linguistics.
- Vrandečić, D.; and Krötzsch, M. 2014. Wikidata: a free collaborative knowledgebase. *Communications of the ACM*, 57(10): 78–85.
- Vu, T.; Iyyer, M.; Wang, X.; Constant, N.; Wei, J.; Wei, J.; Tar, C.; Sung, Y.-H.; Zhou, D.; Le, Q.; et al. 2023. Fresh-llms: Refreshing large language models with search engine augmentation. *arXiv preprint arXiv:2310.03214*.
- Wang, H.; Minervini, P.; and Ponti, E. M. 2024. Probing the Emergence of Cross-lingual Alignment during LLM Training. *arXiv preprint arXiv:2406.13229*.
- Wang, W.; Haddow, B.; Peng, W.; and Birch, A. 2024. Sharing Matters: Analysing Neurons Across Languages and Tasks in LLMs. *arXiv preprint arXiv:2406.09265*.
- Wang, X.; Chen, G. H.; Song, D.; Zhang, Z.; Zhou, D.; Xu, Q.; Xu, X.; Wang, F.; Jin, J.; Liu, B.; and Wang, W. 2023. CMB: Chinese Medical Benchmark. <https://github.com/FreedomIntelligence/CMB>. Xidong Wang, Guiming Hardy Chen, Dingjie Song, and Zhiyi Zhang contributed equally to this work.
- Wei, Q.; Chan, A. J.; Goetz, L.; Watson, D.; and van der Schaar, M. 2024. Actions Speak Louder than Words: Superficial Fairness Alignment in LLMs. In *ICLR 2024 Workshop on Reliable and Responsible Foundation Models*.
- Xu, Y.; Hu, L.; Zhao, J.; Qiu, Z.; Ye, Y.; and Gu, H. 2024. A Survey on Multilingual Large Language Models: Corpora, Alignment, and Bias. *arXiv preprint arXiv:2404.00929*.
- Yang, A.; Yang, B.; Hui, B.; Zheng, B.; Yu, B.; Zhou, C.; Li, C.; Li, C.; Liu, D.; Huang, F.; et al. 2024a. Qwen2 technical report. *arXiv preprint arXiv:2407.10671*.
- Yang, Z.; Wang, D.; Zhou, F.; Song, D.; Zhang, Y.; Jiang, J.; Kong, K.; Liu, X.; Qiao, Y.; Chang, R. T.; et al. 2024b. Understanding Natural Language: Potential Application of Large Language Models to Ophthalmology. *Asia-Pacific Journal of Ophthalmology*, 100085.
- Zhao, A.; Huang, D.; Xu, Q.; Lin, M.; Liu, Y.-J.; and Huang, G. 2024a. Expel: Llm agents are experiential learners. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, 19632–19642.
- Zhao, J.; Ding, Y.; Jia, C.; Wang, Y.; and Qian, Z. 2024b. Gender Bias in Large Language Models across Multiple Languages. *arXiv preprint arXiv:2403.00277*.
- Zhao, J.; Zhang, Z.; Zhang, Q.; Gui, T.; and Huang, X. 2024c. Llama beyond english: An empirical study on language capability transfer. *arXiv preprint arXiv:2401.01055*.
- Zhu, Y.; Moniz, J. R. A.; Bhargava, S.; Lu, J.; Piraviperumal, D.; Li, S.; Zhang, Y.; Yu, H.; and Tseng, B.-H. 2024. Can Large Language Models Understand Context? *arXiv preprint arXiv:2402.00858*.