# Disparities in Multilingual LLM-Based Healthcare Q&A

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#### **Abstract**

Equitable access to reliable health information is vital when integrating AI into healthcare. Yet, information quality varies across languages, raising concerns about the reliability and consistency of multilingual Large Language Models (LLMs). We systematically examine cross-lingual disparities in pre-training source and factuality alignment in LLM answers for multilingual healthcare Q&A across English, German, Turkish, Chinese (Mandarin), and Italian. We (i) constructed Multilingual Wiki Health Care (MultiWikiHealthCare), a multilingual dataset from Wikipedia; (ii) analyzed cross-lingual healthcare coverage; (iii) assessed LLM response alignment with these references; and (iv) conducted a case study on factual alignment through the use of contextual information and Retrieval-Augmented Generation (RAG). Our findings reveal substantial cross-lingual disparities in both Wikipedia coverage and LLM factual alignment. Across LLMs, responses align more with English Wikipedia, even when the prompts are non-English. Providing contextual excerpts from non-English Wikipedia at inference time effectively shifts factual alignment toward culturally relevant knowledge. These results highlight practical pathways for building more equitable, multilingual AI systems for healthcare.

#### 1 Introduction

LLMs are increasingly deployed across healthcare applications, and people seeking health information routinely turn to LLM-based systems for advice and guidance (Yagnik et al., 2024; Yu et al., 2024). Since LLMs are trained primarily on large-scale online data, their responses are shaped by the availability and quality of online health information (Nigatu et al., 2025). However, this information varies markedly across languages, reflecting disparities in health communication, infrastructure, and cultural norms (Tierney et al., 2025; Yang and Valdez, 2025).

Several healthcare benchmarks probe both LLM hallucination and disparity analysis (Agarwal et al., 2024; Koopman and Zuccon, 2023; Kim et al., 2025; Zhu et al., 2019; Samir et al., 2024), but they remain largely English-centric or too coarsegrained to diagnose performance gaps across languages. Moreover, although related, the two concepts operate on different levels of analysis. While hallucination detection focuses on identifying factually incorrect or fabricated content (Kim et al., 2025; Zhang et al., 2025), disparity analysis examines differences in how information is represented or prioritized across linguistic and contextual boundaries, even when the facts themselves may vary across cultural settings (Samir et al., 2024; Ranathunga and de Silva, 2022). Prior work has applied disparity analysis to Wikipedia articles on people and cuisines (Samir et al., 2024; Wang et al., 2025) and to LLM outputs in medicine (Gupta et al., 2025; Restrepo et al., 2025). However, no study has explicitly linked disparities between training data (e.g., Wikipedia) and LLM-generated responses.

In this paper, we introduce a holistic framework to assess how LLM-generated health answers align with factuality and culture across languages. As illustrated in Figure 1, (i) we begin by comparing healthcare-related Wikipedia pages, which is a pretraining corpus for many LLMs (Singhal et al., 2023), across languages to characterize similarities and discrepancies in coverage, phrasing, and citation patterns. From this analysis, (ii) we construct aligned cross-lingual fact sets and use them to generate questions posed to several multilingual LLMs: Llama3.3-70B (Dubey et al., 2024), Qwen3-Next-80B-A3B-Instruct (Yang et al., 2025), and Aya (Dang et al., 2024). Subsequently, (iii) we evaluate the responses for quality and alignment with both English Wikipedia and the corresponding target-language pages. Finally, magenta (iv)we present a case study testing whether providing non-English contextual excerpts at inference

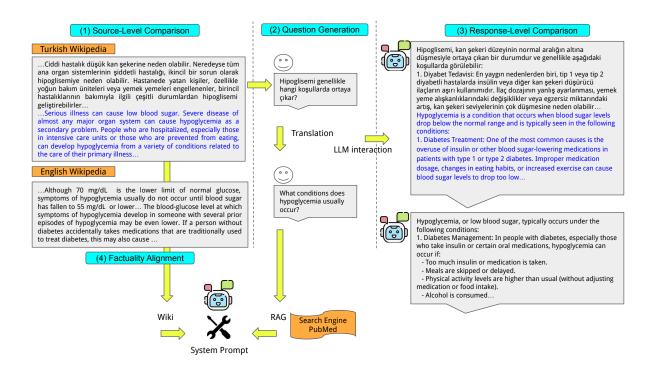


Figure 1: Analyzing source- and response-level disparity and factuality alignment: (1) comparison of Turkish and English Wikipedia pages, (2) fact-based question generation, (3) response factuality evaluation and (4) contextual alignment using Wiki pages and RAG. English translations are shown in blue.

time shifts factual alignment toward locally relevant sources, through the use of contextual information and *Retrieval-Augmented Generation* (RAG). Accordingly, the main contributions of this work can be summarized as follows:

- We introduce **MultiWikiHealthCare**, a multilingual dataset of trending healthcare topics from Wikipedia in English, German, Italian, Turkish, and Chinese, enabling systematic cross-lingual comparisons at both source and response levels <sup>1</sup>.
- Wikipedia analysis reveals major disparities: Chinese pages show the least factual overlap with English, and German pages more often cite regional sources, while others rely on international ones.
- Analysis of responses shows a pronounced English-centric alignment: responses more closely track English Wikipedia than sametopic pages in other languages. When questions are posed in English, similarity to non-English source pages drops further. While this may be acceptable for universal medical facts

but problematic for culturally specific knowledge where practices and guidelines vary.

 Our case study demonstrates that providing non-English contextual excerpts can shift models toward locally relevant information at inference time.

## 2 Related Work

Several studies have examined how prompt design affects the factual reliability of LLMs in medical Q&A. Koopman and Zuccon (2023); Kim et al. (2025) showed that prompt phrasing and cues significantly influence factual accuracy, while Sayin et al. (2024) found that prompt engineering enhances physician–LLM collaboration and error correction. Kaur et al. (2024) reported that LLMs rarely contradict medical facts but often fail to challenge false ones. Extending this to multilingual settings, Jin et al. (2024) observed substantial cross-lingual differences in accuracy, consistency, and verifiability.

Agarwal et al. (2024) introduce the MedHalu dataset and the accompanying MedHaluDetect framework for detecting fine-grained factual hallucinations in responses by LLMs. MedHalu consists of healthcare-related questions in English from HealthQA (Zhu et al., 2019), LiveQA (Abacha

<sup>&</sup>lt;sup>1</sup>Our dataset and code will be released publicly after review.

et al., 2017) and MedicationQA (Abacha et al., 2019). The authors utilized fine-grained hallucination types proposed by Zhang et al. (2025), namely, input-conflicting, context-conflicting and fact-conflicting and then generated artificially hallucinations on the answers based on this taxonomy by using GPT-3.5 (Achiam et al., 2023). They evaluated Llama (Touvron et al., 2023), GPT-3.5 and GPT-4 (Touvron et al., 2023) as evaluators and compared them against layman and expert users. They found that the LLMs underperformed relative to expert and layman users in detecting hallucinations.

For cross-lingual factual analysis, Samir et al. (2024) proposed InfoGap which is a GPT-4 based framework that decomposes and aligns multilingual Wikipedia facts, applied to biographies from the LGBTBio Corpus (Park et al., 2021). In the medical domain, Gupta et al. (2025) analyzed LLM consistency and empathy across translated mental health Q&A, while Restrepo et al. (2025) developed a multilingual ophthalmology benchmark and introduced CLARA, a RAG-based method for debiasing inference. Schlicht et al. (2025) compared LLM outputs across languages, identifying discrepancies in detail, numerical accuracy, and citation reliability. Unlike prior healthcare benchmarks, we investigate the correlation between factual knowledge potentially acquired during pretraining and the factual alignment of LLM-generated responses across languages. Furthermore, we extend this analysis to culturally diverse languages.

# 3 Multilingual Wiki Health Care

Existing benchmark datasets largely focus on monolingual or general-purpose tasks, lacking the specificity needed to assess how pretraining sources affect multilingual answer quality in specialized domains such as healthcare. To address this gap, we introduce **MultiWikiHealthCare**, a multilingual, health-focused Q&A dataset. It is derived from Wikipedia, pretraining source for LLMs. Figure 2 presents the pipeline for constructing the dataset.

Vaccination, Weight Loss, Diet, Obesity, Nutrition, Flu, Cold, Influenza, Ebola, COVID, Allergy, Smoking, Pain, Depression, Diabetes, Cardiovascular Disease, Cancer

Table 1: List of the main health topics which we used for searching trending sub-topics from Google Trends.

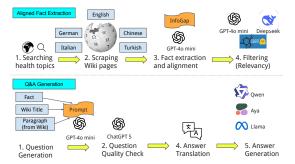


Figure 2: MultiWikiHealthCare - Pipeline for Q&A construction

## 3.1 Construction of Aligned facts

## 3.1.1 Healthcare Topics

To construct MultiWikiHealthCare, we first curated a list of trending and controversial health topics<sup>2</sup> by using Google Trends,<sup>3</sup> and Wikipedia's list of controversial issues in science, biology, health,<sup>4</sup> and related surveys (Schlicht et al., 2024). These topics formed the basis of content collection. Table 1 presents the main health topics in the dataset. We used Google Trends to identify subtopics from related entities trending between 2004 and 2025 across global and country-level search data (U.S., U.K., Turkey, Germany, Italy, and China). Across all languages, we identified 1193 unique entities. Figure 3 shows a word cloud of these subtopics. Symptoms, causes, and diseases are common entities across languages while some entities are not specific to the healthcare domain.



Figure 3: Word cloud of trending subtopics derived from Google Trends (2004–2025) across global and six countries. The size of each blob corresponds to the number of languages in which the subtopic appears.

#### 3.1.2 Scraping Wikipedia Pages

We used Llama 3.3-70B, prompted as in Figure 4 and served through the vLLM inference frame-

<sup>&</sup>lt;sup>2</sup>Search was done in 2025

https://trends.google.com/trends/explore

<sup>4</sup>http://bit.ly/4m59RTa

You are an intelligent assistant that identifies whether an entity is related to healthcare. When given an entity (e.g., a term, organization, person, product, etc.), first determine whether it is related to healthcare. If it is related to healthcare, return the URL of its Wikipedia page (e.g., https://en.wikipedia.org/wiki/ENTITY\_NAME). If it is not related to healthcare, return False. Consider healthcare to include: medicine, medical devices, hospitals, health policy, public health, pharmaceuticals, biotechnology, mental health, nutrition, diet, food safety, and functional foods.

Figure 4: Prompt for finding Wikipedia pages

work (Kwon et al., 2023), to (i) filter out entities not related to healthcare and (ii) link the remaining entities to their corresponding Wikipedia pages. After removing duplicates, we retained 918 unique Wikipedia pages.

Wikipedia page titles often differ across languages, especially when scripts differ or the title is a common noun rather than a proper name (e.g., English/Italian "Nausea" vs. German "Übelkeit"). Therefore, we retrieved interlanguage titles using the open-source Wikipedia API <sup>5</sup>. Pages available only in English were excluded as they are unsuitable for comparative analysis, yielding 815 titles present in English and at least one additional language. A subsequent manual review showed that some pages referred to 'films' or 'people'. We collected category metadata from English Wikipedia and removed pages whose categories included 'people', 'film', or 'doctoral degree'. The final Englishlanguage subset comprises 799 pages.

#### 3.1.3 Fact Extraction and Alignment

Language Pair	F1-Macro	Random
$en \leftrightarrow tr$	0.841	0.574
$en \leftrightarrow zh$	0.724	0.535
$en \leftrightarrow de$	0.684	0.479
$en \leftrightarrow it$	0.638	0.538

Table 2: Results comparison between human annotators and InfoGap predictions and random guess

From the Wikipedia articles, we extracted factual facts together with their supporting paragraphs as evidence. We categorized these facts into two groups: (1) Cross-lingual overlapping facts, where the same factual content appears in both English and non-English version; and (2) Language-specific facts, which are unique to the non-English article without an English counterpart. The first

group is used to construct the Q&A dataset and the second is part of Wikipedia analysis in Section 4.1.

Fact extraction and alignment were performed with InfoGap (Samir et al., 2024; Wang et al., 2025), a state-of-the-art framework for crosslingual fact extraction and alignment on Wikipedia. The framework combines OpenAI LLMs with a hubness-based correction technique to improve cross-language alignment accuracy. Because a single Wikipedia page can contain hundreds of atomic facts, running OpenAI models at corpus scale is costly (Samir et al., 2024). While the latest Info-Gap (Wang et al., 2025) employs GPT-40 (Achiam et al., 2023), we adopted GPT-4o-mini (Hurst et al., 2024) as the backbone model, which is approximately 10% less expensive than GPT-40. To assess reliability on our corpus, we sampled 50 facts per language following the InfoGap evaluation protocol. Annotations were conducted by volunteer native speakers using the official InfoGap guidelines. Our results (see Table 2) are comparable to those reported by Samir et al. (2024), which outperform a random prediction<sup>6</sup>.

Example	Relevancy
Vitamin C exhibits low/acute toxicity.	Relevant
Non-radioactive iodine can be taken in the form of potassium iodide tablets.	Relevant
If a dog was sick, they would get better food.	Irrelevant
Routine chickenpox vaccination was introduced in the United States.	Irrelevant

Table 3: Examples of relevant and irrelevant facts.

#### **3.1.4** Selecting Relevant facts

You are given a factual statement from Wikipedia. Decide whether it would be useful for someone seeking health-related information. **Relevant** means it provides useful health-related information such as symptoms, causes, risk factors, treatments, prevention, prognosis, lifestyle advice, or other patient-centered context.

**Not relevant** means it is historical, administrative, technical, or other information that is not directly useful for someone with health-related queries.

Task: Respond with only "Relevant" or "Not relevant".

Input: [Single factual statement]
Response: Relevant / Not relevant

Figure 5: Prompt for selecting relevant facts

After cross-lingual extraction and alignment, we retained only bidirectionally matched facts: the intersection of the two directions for each language

<sup>5</sup>https://github.com/martin-majlis/ Wikipedia-API

<sup>&</sup>lt;sup>6</sup>In (Samir et al., 2024), random guessing outperformed Natural Language Inference transformers.

Language	LLM	Mono TF	Cross TF
en	82.69	86.49	88.44
tr	77.89	83.46	84.20
zh	68.47	77.02	72.11
de	76.67	70.88	81.32
it	71.96	72.00	83.33

Table 4: Comparison of transformers (TF): cross-lingual and mono-lingual against GPT-4o-mini in terms of F1-macro.

pair (e.g. en<->tr). Although the facts are atomic, InfoGap returns the aligned source sentences in both languages. We then located the paragraphs containing these sentences and matched each fact with its corresponding bilingual evidence.

We observed that not all Wikipedia-derived facts are relevant to health information seekers (e.g., some facts are historical or highly technical). The examples of relevant/irrelevant facts are given in Table 3. To remove such content, we implemented a relevance filter. As the corpus is large, running GPT-40-mini over all facts would be time-consuming and costly. To lower inference cost while preserving quality, we distilled GPT-40-mini's judgments (and DeepSeek-R1 (Guo et al., 2025)'s for Chinese) into a smaller model.

To calibrate a shared understanding of the relevance task and design the prompt for labeling, we performed annotations. The annotators first labeled at least 25 English samples, with two annotators per sample. We held regular discussions to refine the annotation guidelines. Inter-annotator agreement, measured by Krippendorff's alpha (Ford, 2004) on a subset of 52 samples, was  $\alpha=0.72$ . Each annotator then labeled 50 samples in their respective language. The annotations form the test set for comparing the LLMs with transformer-based models across languages. Furthermore, we finalized the labeling prompt in English (given in Figure 5). The native speakers translated it into the other languages.

We annotated 2,000 Turkish and English, 4,000 German, 3,000 Italian, and 3,000 Chinese samples with LLMs. GPT-40-mini was used for all except Chinese, which was labeled with DeepSeek-R1 due to poor alignment. Each dataset was randomly split into 70% training and 30% development sets. We fine-tuned language specific transformers on their monolingual dataset (Roberta-base (Liu et al., 2019) for English, BertTurk (Schweter, 2020) for Turkish, German BERT (Devlin et al., 2019) for

German) and Chinese BERT (Devlin et al., 2019) for the Chinese dataset. Additionally, for each non-English dataset was combined with the English samples, and then XLM-Roberta <sup>7</sup> was fine-tuned. All models were fine-tuned with a learning rate of 2e-5, for 3 epochs, and a batch size of 16. The models with the best F1-macro scores (see Table 4) were selected. Except for Chinese, cross-lingual models performed best and were used as relevancy classifiers. Finally, we labeled the corpora with the fine-tuned transformers (Wolf et al., 2020) and discarded unrelated samples.

#### 3.2 Question and Answer Generation

You are a person seeking health-related information. Task: Using the provided Fact from the ENTITY Wikipedia page and the accompanying Paragraph for context, generate only one natural question. The question must be directly related to the given Fact.

The answer to the question must be fully answered by the information in the Paragraph (do not add outside knowledge).

The question should sound like something a person curious about health might naturally ask.

Keep the question concise and easy to understand.

Fact:

{fact}
Paragraph:

{paragraph}

**Generated Question:** 

Figure 6: Prompt for health-care question generation

I want to analyze whether the LLM has generated a sensible question based on the prompt I provided. Here is the prompt:

"'You are someone searching for health information that can help you make decisions about your own or someone else's health. Task: Using the information provided on the entity Wikipedia page and the related paragraph as context, generate only one natural question.

- The question must be directly related to the given information.
- The question must be answerable solely based on the information in the paragraph (do not add knowledge from external sources).
- The question must be something a person curious about health-related information would naturally ask.
- The question must be clear and easy to understand. Input:

Fact: [A single factual/informational sentence]

Paragraph: [Paragraph]

Output: [Generated question]"

Now, I will give you a CSV file containing a set of examples, each row representing one instance. The columns in the file are as follows:

"fact": the information

"evidence": the paragraph from which the fact is derived

" $llm\_output"$ : the question generated by the LLM according to the {LANG} prompt

Please carefully examine the CSV file and evaluate the quality of the generated question for each example. Use only the quality criteria defined in the prompt above; do not introduce any additional criteria. Then, provide me a detailed analysis and a technical report in English.

Figure 7: Prompt for quality check with GPT-5

<sup>&</sup>lt;sup>7</sup>FacebookAI/xlm-roberta-base

**Question Generation.** We generated synthetic health-related questions using a prompt that instructed GPT-40-mini to act as a health information seeker. The prompt (Figure 6) took as input a Wiki page name, a fact, and its paragraph. From the dataset mentioned in Section 3.1.4, we sampled 1,100 samples per language to generate.

Formally, let each data instance be represented as  $d=(f_x,f_{en},p_x,p_{en})$ , where  $f_x$  is a fact in Language X,  $f_{en}=\{f_{en}^1,\ldots,f_{en}^n\}\ (n\geq 1)$  is its aligned English fact(s),  $p_x$  is the paragraph in Language X containing  $f_x$ , and  $p_{en}$  is the aligned English paragraph(s). Given  $(f_x,p_x,p_{en})$ , we used GPT-40-mini to generate a question  $q_x$  in Language X and then translated it to English with Google Translate to get the question pair.

We evaluated the quality of the generated questions based on the LLM-as-a-Judge technique (Gu et al., 2025) using ChatGPT-5 (Extended Thinking) (OpenAI, 2025) with the prompt provided in Figure 7. This prompt instructed ChatGPT-5 to execute a deterministic Python-based evaluation pipeline within its data-analysis sandbox (OpenAI, 2025). The model applied four binary criteria to each question: (1) relevance to both the input fact and the source paragraph, (2) answerability based solely on the paragraph, (3) alignment with natural health-seeker intent, and (4) clarity of expression.

To assess alignment with human judgments, we sampled 20 items per language and compared ChatGPT-5's decisions to native-speaker annotations. The agreement ranged from 44% to 76% (highest for Turkish, lowest for German). ChatGPT-5 consistently accepted fewer questions than human annotators, indicating a more conservative criterion. Based on this preliminary evidence, we used ChatGPT-5 as a pre-filter for question quality.

Answer Generation. To generate answers, we deliberately use multilingual, open-weight LLMs from distinct organizations to mitigate model-family bias in our evaluation. Specifically, we include Llama 3.3–70B (Meta; an upgraded release of Llama 3 (Grattafiori et al., 2024)), Qwen (Qwen3-Next-80B-A3B-Instruct) (Yang et al., 2025) from Alibaba Cloud and Aya (Expanse-32b) from Cohere (Dang et al., 2024). We discarded DeepSeek-R1 from the analysis due to its size and cost. We run Aya locally on a GPU, while the other models are accessed via APIs through Hugging Face Inference <sup>8</sup>. For all LLMs, we set the

Language	#Sample
Turkish	854
German	997
Italian	502
Chinese	548

Table 5: Final number of the samples per language in the dataset for analysis of LLM responses

temperature to 1 and the maximum token length to 4096.

## 4 Experiments and Results

Main research question in this paper is how disparities across languages in pre-training data contribute to inconsistencies in LLM answers for multilingual healthcare Q&A. We first characterize healthcare-related Wikipedia pages; we then evaluate each model's answers for cross-lingual factual alignment against evidence extracted from the corresponding pages.

# 4.1 Comparison of Wikipedia Pages

			Aligned facts (%)		
Language	Paragraphs	Facts	$\mathbf{en} \to \mathbf{Target}$	$\textbf{Target} \rightarrow \textbf{en}$	
en	26,752	20,5468	NA	NA	
tr	8,554	47,711	%33.79	%91.82	
zh	728	6,155	%6.98	%59.46	
de	18,284	11,8268	%23.36	%98.44	
it	14,846	96,342	%26.73	%54.23	

Table 6: Statistics of paragraphs, facts and aligned facts on 502 Wiki pages of MultiWikiHealthCare. NA is Not Applicable. Many English facts don't exist in other language editions. Chinese Wiki has the lowest aligned facts with the English wiki pages.

	Sections	Paragraphs	Facts	Links
tr-en	$1.51\times10^{-96}$	$2.88 \times 10^{-87}$	$1.72 \times 10^{-106}$	$6.24 \times 10^{-68}$
de-en	$2.48 \times 10^{-22}$	$3.39 \times 10^{-28}$	$1.99 \times 10^{-48}$	$7.14 \times 10^{-79}$
zh-en	$1.44 \times 10^{-77}$	$1.39 \times 10^{-141}$	$1.59 \times 10^{-133}$	$6.55 \times 10^{-60}$
it-en	$1.35 \times 10^{-50}$	$1.80 \times 10^{-50}$	$9.11 \times 10^{-70}$	$4.75 \times 10^{-74}$

Table 7: The English (en) Wiki pages contain statistically more information than their other editions (Paired t-test p value).

We examine the amount of information presented in Wikipedia articles across languages. To this extent, we compare number of sections, paragraphs, facts and external links that the articles cited.

As articles are typically organized into sections that aid navigation and reflect the logical structure

package\_reference/inference\_client

<sup>8</sup>huggingface.co/docs/huggingface\_hub/en/

of the content, we use the number of sections as a simple, language-agnostic proxy. Accordingly, we measure and compare section counts across languages. We use Beautiful Soup 9 to parse each article's HTML. Next, we count the paragraphs and facts obtained through InfoGap, as described in Section 3.1.3, with the results summarized in Table 6. Lastly, we analyze the references cited by Wikipedia editors to examine how reference preferences vary across languages. References serve as important indicators of information diversity and reliability. We restrict our analysis to entries with articles in all target languages. We begin by comparing the number of references per article across languages and then compare the sources cited by each edition. Additionally, we extract the sources of the external links by using tldextract <sup>10</sup>.

As shown in Table 7, English Wikipedia contains significantly more information than other languages (paired t-test (Ross and Willson, 2017)). It has the most paragraphs and extracted facts, many without counterparts elsewhere. Chinese Wikipedia shows the fewest English-aligned facts, likely because English Wikipedia benefits from a broader, more global editor base. Across languages, domains associated with the National Institutes of Health and the Centers for Disease Control and Prevention are common. Other highfrequency domains are news outlets, scholarly journals, and file archives. Distinctively, the German edition also cites national sources (e.g., rki.de, aerzteblatt.de). In summary, citation coverage and practices vary substantially across language editions, reflecting differences in local information ecosystems and editorial norms.

## 4.2 Analyzing Answers

As our tools are English-based, all non-English answers and evidence were translated into English for scoring. We begin the analysis with the response length. Across non-English prompts, Qwen consistently produced longer answers, reflecting a tendency toward more elaborated outputs. For Chinese questions, most models gave brief answers, except Qwen, likely reflecting its stronger Chinese-language training.

We evaluate English and non-English answers against their Wikipedia evidence using Align-Score (Zha et al., 2023), which measures sentence-level factual consistency via a RoBERTa alignment

Query	Llama		Aya		Qwen	
	non-en	en	non-en	en	non-en	en
tr	27.44	30.89	17.78	22.62	14.45	18.31
en	16.96	21.64	15.03	20.02	14.04	18.28
de	18.13	18.56	16.26	17.92	13.64	16.59
en	16.85	18.68	14.69	17.37	13.38	17.02
zh	22.39	28.13	20.22	26.78	17.45	22.71
en	20.09	26.23	16.90	23.81	15.58	21.72
it	20.16	23.51	16.40	20.94	14.12	18.41
en	16.65	21.64	15.04	19.97	13.54	17.97

Table 8: Factual alignment between answers and Wiki excerpts in the source language (non-en) and English (en), measured by AlignScore. Non-English content was translated into English. Overall, answers align more closely with English pages, while English questions show lower similarity to source-language references.

model (Liu et al., 2019). For questions with multiple aligned English passages, we report the passage with the highest AlignScore.

Answers from conversational LLMs frequently include background and discursive material beyond the minimal facts needed to address a question (Xu et al., 2022), whereas our evidence snippets are concise and fact-dense. Consequently, absolute AlignScores tend to be modest; we interpret them as a relative proxy for factual alignment rather than a comprehensive quality metric. Hence, we expect higher scores when a response is factually similar to the source-language reference, and lower scores otherwise.

Table 8 shows that the generated answers are factually close to English references in most cases. However, when questions are asked in English, factual alignment decreases for all languages except German. In particular, factual alignment is higher when evaluated against source-language evidence than against evidence from the English Wikipedia pages. This finding is consistent with prior work showing that responses to equivalent prompts can diverge across English and non-English settings (Jin et al., 2024; Schlicht et al., 2025).

Lastly, we used the Spearman correlation coefficient (Wissler, 1905) ( $\rho$ ) to assess the relationship between Wikipedia page quality and LLM answer quality across languages. For this analysis, we additionally measured the relevancy of the answers to the questions by using ragas (Es et al., 2024) with GPT-40-mini. Correlations were generally weak to moderate ( $\rho$  = 0.01–0.34). For Italian, Turkish, and German, the relationships were negligible or weak ( $\rho$  < 0.20), suggesting that the number of sections, paragraphs, or facts in the corresponding

<sup>9</sup>https://beautiful-soup-4.readthedocs.io

<sup>10</sup>https://github.com/john-kurkowski/tldextract

Wikipedia entries had limited predictive power for the factuality, relevancy, or length of model outputs. In contrast, the correlations to the factuality scores for Chinese were higher, reaching moderate strength for Aya ( $\rho \approx 0.34$ ) and Llama ( $\rho \approx 0.30$ ), and weak-to-moderate for Qwen ( $\rho \approx 0.27$ ). Wikipedia content quality in Chinese Wikipedia might have positive effect on factuality of the responses.

# 4.3 Case Study: Factuality Alignment

Target	Method	Llama		Aya		Qwen	
8		non-en	en	non-en	en	non-en	en
tr	Base	17.28	22.46	15.34	20.91	14.24	18.88
	Wiki	78.67	59.21	41.52	35.60	78.53	58.48
	RAG	23.51	33.71	15.55	21.45	15.91	27.10
de	Base	16.89	18.70	14.71	17.41	13.41	17.02
	Wiki	80.68	27.62	34.73	18.43	72.72	20.86
	RAG	23.75	34.69	15.89	19.84	15.65	30.21
zh	Base	22.44	28.13	16.89	23.87	15.47	21.74
	Wiki	83.14	51.39	43.67	34.40	77.99	46.95
	RAG	29.83	43.65	17.98	25.62	21.78	36.49
it	Base	16.84	21.84	14.37	16.70	13.56	18.17
	Wiki	76.78	41.03	37.10	26.79	81.55	40.05
	RAG	24.56	40.05	15.31	21.06	15.83	20.29

Table 9: When the excerpt from non-English (nonen) Wiki pages is translated into English, the answers aligned more to the source context. With RAG, that is opposite.

Response alignment with high-resource knowledge sources such as English Wikipedia is often desirable, as health information in low-resource languages is often limited or lower quality (Weissenberger et al., 2004; Lawrentschuk et al.; Davaris et al., 2017). In such cases, knowledge from high-resource languages can effectively complement existing gaps. However, certain scenarios demand more localized or domain-specific information, where English-centric knowledge may not be sufficiently reliable or contextually appropriate for target users (Yang and Valdez, 2025). To explore this, we evaluate: (1) providing contextual information into prompt and (2) RAG (Lewis et al., 2020).

We adopt a RAG prompt from HuggingFace <sup>11</sup> for both setups. For the first method, we incorporate translated excerpts from non-English Wikipedia pages that are semantically aligned with the given question. For RAG, we scrape PubMed articles <sup>12</sup> using Paperscraper <sup>13</sup>, querying by entity

and nationality keywords (e.g., allergy + Turkish) to obtain culturally specific information. We discard entities with fewer than 50 retrieved PubMed articles and perform analysis on the rest. The RAG model is built using the BM25-Sparse retriever (Lù, 2024). We incorporate top 10 articles that returned from the retriever into the context.

We compare the approaches against the baseline where the LLM responds to questions posed in English (Section 4.2). Both approaches improve reference alignment by producing more factual and concise answers than the baseline. As shown in Figure 9, LLMs incorporating excerpts from Wikipedia produce responses that align more closely with non-English references, while with RAG they align more with English references. RAG results contain usually noisy context, leading to cases where LLMs are uncertain about their answers. Additionally, due to the increased prompt length, Aya was unable to generate responses for a few examples. Explicit, high-quality contextual information might be crucial for effective alignment. In future work, we plan to explore more advanced information retrieval and RAG methods to improve contextual relevance.

#### 5 Conclusion and Future Work

We introduced MultiWikiHealthCare, a multilingual benchmark for studying disparities across languages in healthcare question answering. By pairing popular user queries with language-specific Wikipedia evidence, we quantified how differences in encyclopedic coverage (e.g., structure, citations, and fact availability) manifest in model behavior. Our results show substantial differences across languages: LLMs often privilege English-centric evidence, while conditioning generation on sourcelanguage excerpts shifts grounding toward locally relevant knowledge. Taken together, these findings highlight a practical path for improving equity in multilingual healthcare Q&A, explicitly anchor answers in the user's language of reference rather than defaulting to English.

Future work will extend sources beyond Wikipedia to clinical and public health materials, adopt multilingual factuality metrics with native-speaker review, and scale to more data, languages, and multi-turn dialogue.

<sup>11</sup>https://huggingface.co/blog/ngxson/make-your-own-rag

<sup>12</sup>https://pubmed.ncbi.nlm.nih.gov/

<sup>13</sup>https://github.com/jannisborn/paperscraper

#### **Ethics Statement and Limitations**

This study examines informational disparities in LLMs applied to healthcare contexts across multiple languages. All analyses were conducted using publicly available data from Wikipedia. Therefore, no private, sensitive or personally identifiable health information was accessed or processed. All evaluations were performed solely for research purposes and none of the LLMs analyzed should be solely used to provide medical device. We acknowledge that the disparities observed across languages and Wikipedia may reflect broader inequities in global health communication and data representation. Through this analysis, we aim to promote more equitable and fair multilingual health-care applications.

Furthermore, our work has several limitations: (i) AlignScore is English-centric, so we translate non-English evidence and answers into English, which may introduce artifacts; (ii) Wikipedia is used as the proxy reference for constructing questions and evidence, and neither Wikipedia excerpts nor model outputs were independently factchecked; (iii) budget constraints (paid APIs for most models) and limited availability of native speakers restricted us to a relatively small number of Q&A pairs and single-turn interactions; and (iv) because LLMs are trained in heterogeneous sources, their knowledge does not need to align with Wikipedia, so our findings reflect alignment relative to Wikipedia rather than clinical correctness.

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