

AN EMPIRICAL INVESTIGATION OF BIAS TRANSMISSION MECHANISMS IN LARGE-SCALE LANGUAGE MODELS TRAINED ON MULTILINGUAL LOW-RESOURCE DATA STREAMS

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Abstract - The rapid advancement of multilingual large language models (LLMs) has significantly improved cross-lingual information access and natural language understanding. However, these models are often trained on unevenly distributed multilingual datasets, where high-resource languages dominate low-resource ones, leading to potential bias in information retrieval and generation. This study presents an empirical investigation of bias transmission mechanisms in large-scale multilingual LLMs, with a particular focus on systems integrated with retrieval-augmented generation (RAG) frameworks. The research adopts a controlled experimental design in which semantically equivalent queries are executed across multiple languages to analyze variations in retrieved documents and generated responses. A multilingual dataset comprising both high-resource and low-resource languages is utilized to evaluate model behavior. The study introduces quantitative and qualitative evaluation metrics, including retrieval language distribution, response similarity, information completeness, and contextual relevance. Experimental results reveal that multilingual LLMs exhibit a strong preference for high-resource language sources during retrieval, which significantly influences the quality and completeness of generated responses. Furthermore, bias is observed to propagate through multiple stages, including training data, retrieval processes, and response generation. The findings highlight critical challenges in achieving equitable information representation and emphasize the need for improved multilingual training strategies and bias-aware retrieval mechanisms in large-scale language models.

Key Words: Multilingual Large Language Models, Bias Transmission, Low-Resource Languages, Retrieval-Augmented Generation, Cross-Lingual Information Retrieval, Information Disparity

1. INTRODUCTION

The rapid evolution of multilingual large language models (LLMs) has transformed the landscape of natural language processing by enabling systems to process, retrieve, and generate information across multiple languages within a unified framework. These models are increasingly deployed in applications such as search engines, conversational

agents, and knowledge retrieval systems, where they act as intermediaries between users and global information resources. However, despite their capabilities, multilingual LLMs often inherit structural imbalances from the data on which they are trained, leading to unequal representation of languages and knowledge sources. This section introduces the background, problem context, research gaps, objectives, and contributions of the study, focusing on bias transmission mechanisms in multilingual environments.

1.1 Background

The development of multilingual LLMs has been driven by the need to support global communication and information access across diverse linguistic communities. Advances in transformer-based architectures have enabled models to learn shared representations across languages, facilitating cross-lingual understanding and transfer learning (Vaswani et al., 2017). As a result, modern LLMs are capable of handling dozens or even hundreds of languages, significantly improving accessibility to digital knowledge systems.

1.1.1 Growth of Multilingual LLMs

Multilingual LLMs have evolved through large-scale pre-training on multilingual corpora collected from web data, books, and online repositories. These models leverage shared embedding spaces to transfer knowledge from high-resource languages to low-resource ones, improving performance in multilingual tasks such as translation and question answering. However, the growth of such models has also amplified concerns regarding the uneven distribution of training data, as high-resource languages dominate the learning process, influencing model behavior and knowledge representation (Devlin et al., 2019).

1.1.2 Role in Global Information Access

Multilingual LLMs play a critical role in enabling global access to information by bridging language barriers in digital ecosystems. They allow users to retrieve and interact with knowledge regardless of their native language, supporting inclusive communication and knowledge dissemination. Nevertheless, the effectiveness of these systems depends on the availability and quality of multilingual data, which varies

significantly across languages, potentially limiting equitable access to information (Joshi et al., 2020).

1.1.3 Persistent Imbalance Between High-Resource and Low-Resource Languages

Despite technological advancements, a persistent imbalance exists between high-resource and low-resource languages in NLP systems. High-resource languages benefit from abundant digital data and well-developed linguistic tools, whereas low-resource languages often lack sufficient representation. This disparity affects model performance, leading to differences in accuracy, completeness, and contextual understanding across languages (Hedderich et al., 2021).

1.2 Problem Statement

Although multilingual LLMs aim to provide equitable information access, they often exhibit biases that arise from data imbalances and system design. These biases influence how information is retrieved and presented, raising concerns about fairness and reliability in multilingual AI systems.

1.2.1 Bias in Training Data and Retrieval Systems

Bias in multilingual LLMs originates primarily from the uneven distribution of training data and the mechanisms used in retrieval systems. Since models learn patterns from available data, the dominance of certain languages in training corpora leads to stronger representations for those languages. Additionally, retrieval systems may prioritize documents from high-resource languages due to their higher availability and indexing frequency (Bender et al., 2021).

1.2.2 Unequal Information Representation Across Languages

The imbalance in data distribution results in unequal information representation across languages. Multilingual LLMs may provide more detailed and accurate responses in languages with extensive datasets while generating less comprehensive outputs for underrepresented languages. This disparity can affect users' access to reliable information and reinforce existing inequalities in digital knowledge systems (Hovy and Spruit, 2016).

1.2.3 Language Preference in LLM Outputs

Language preference refers to the tendency of LLMs to favor certain languages during retrieval and response generation. In multilingual settings, models may default to high-resource languages when relevant information is scarce in the query language, thereby influencing the diversity and neutrality of generated outputs (Conneau et al., 2020).

2. RELATED WORK

The study of multilingual large language models (LLMs) and bias transmission is grounded in a rich body of research spanning natural language processing (NLP), machine learning, and information retrieval. This section reviews key developments in LLM architectures, multilingual modeling techniques, bias in AI systems, and retrieval-augmented frameworks, with particular emphasis on challenges related to multilingual bias and information disparity.

2.1 Evolution of LLMs and Multilingual NLP

The field of NLP has undergone a significant transformation with the introduction of deep learning techniques, particularly transformer-based architectures, which have enabled the development of large-scale language models capable of handling complex linguistic tasks.

2.1.1 Transformer-Based Models

Transformer-based models represent a major advancement in NLP due to their ability to capture long-range dependencies in text using self-attention mechanisms. Unlike earlier sequence-based models, transformers process entire sequences in parallel, improving efficiency and contextual understanding. This architecture has become the foundation for modern LLMs, enabling large-scale pre-training on massive corpora and significantly enhancing performance across tasks such as translation, summarization, and question answering (Vaswani et al., 2017).

2.1.2 Cross-Lingual Learning

Cross-lingual learning has emerged as a key technique in multilingual NLP, allowing models to transfer knowledge across languages by learning shared semantic representations. This approach enables models trained on high-resource languages to generalize to low-resource languages, reducing the need for language-specific models. Cross-lingual embeddings and multilingual pre-training strategies have played a crucial role in enabling LLMs to operate effectively in multilingual environments (Ruder, Vulić and Søgaard, 2019).

2.2 Multilingual Language Models

Multilingual language models are designed to process multiple languages within a single architecture, leveraging shared representations to enable cross-lingual tasks and improve accessibility to language technologies.

2.2.1 Shared Embeddings and Transfer Learning

A fundamental concept in multilingual models is the use of shared embedding spaces, where words or sentences from different languages are mapped into a common vector space. This allows semantically similar concepts across languages to be represented closely, facilitating cross-language

understanding. Transfer learning further enhances this capability by enabling knowledge learned from high-resource languages to improve performance in low-resource languages, making multilingual models more efficient and scalable (Conneau et al., 2020).

2.2.2 Performance Imbalance Across Languages

Despite these advancements, multilingual models often exhibit uneven performance across languages. High-resource languages benefit from larger training datasets, resulting in better accuracy and richer contextual understanding. In contrast, low-resource languages often suffer from limited representation, leading to reduced model performance and less reliable outputs. This imbalance remains a significant challenge in multilingual NLP (Pires, Schlinger and Garrette, 2019).

2.3 Bias in AI and NLP Systems

Bias in artificial intelligence has become a critical area of research, particularly as AI systems are increasingly deployed in real-world applications that influence decision-making and information access.

2.3.1 Data Bias

Data bias arises when training datasets are imbalanced or unrepresentative of the diversity present in real-world scenarios. In NLP, this often occurs when certain languages, cultures, or topics are overrepresented in the training data. As a result, models may learn skewed patterns and reproduce these biases in their outputs, affecting fairness and reliability (Barocas, Hardt and Narayanan, 2019).

2.3.2 Linguistic and Cultural Bias

Linguistic and cultural biases emerge when AI systems reflect dominant language structures or cultural perspectives embedded in the data. Multilingual LLMs may prioritize narratives and viewpoints associated with widely represented languages, potentially marginalizing less-represented cultures and linguistic communities. Such biases can influence how information is interpreted and presented, raising concerns about inclusivity in AI systems (Mehrabi et al., 2021).

2.4 High- vs Low-Resource Language Challenges

The distinction between high-resource and low-resource languages is a fundamental issue in multilingual NLP, influencing both model development and performance outcomes.

2.4.1 Data Scarcity

Low-resource languages often lack sufficient digital text data, annotated corpora, and linguistic tools required for training robust NLP models. This scarcity limits the ability of

machine learning systems to learn accurate linguistic patterns, resulting in weaker performance compared to high-resource languages that have abundant data (Joshi et al., 2020).

2.4.2 Model Generalization Issues

Due to limited training data, models trained on low-resource languages may struggle to generalize across different contexts and tasks. Even with cross-lingual transfer learning, the lack of diverse and high-quality data can lead to incomplete or inconsistent representations, affecting the reliability of model outputs in these languages (Hedderich et al., 2021).

2.5 Retrieval-Augmented Generation (RAG)

Retrieval-Augmented Generation (RAG) has emerged as a powerful framework for enhancing the capabilities of language models by integrating external knowledge sources during response generation.

2.5.1 Architecture and Advantages

RAG systems combine a document retriever with a generative language model. The retriever identifies relevant documents from a knowledge base, and the generator uses this information to produce contextually enriched responses. This approach improves factual accuracy, reduces reliance on memorized knowledge, and enables dynamic access to up-to-date information, making it particularly useful for knowledge-intensive tasks (Lewis et al., 2020).

2.5.2 Multilingual Retrieval Limitations

In multilingual settings, RAG systems face challenges related to uneven document distribution across languages. Retrieval mechanisms may favor documents written in high-resource languages due to their greater availability, leading to biased information selection. This limitation can affect the diversity and accuracy of generated responses, especially for queries in low-resource languages (Asai et al., 2021).

2.6 Existing Studies on Multilingual Bias

Recent research has increasingly focused on understanding how multilingual LLMs handle information across different languages and identifying patterns of bias in their outputs.

Empirical studies have shown that multilingual LLMs often generate different responses for semantically equivalent queries across languages. These differences may manifest in terms of response length, detail, and factual accuracy, indicating inconsistencies in knowledge representation and model behavior across languages (Blodgett et al., 2020).

A recurring finding in multilingual bias research is the dominance of high-resource languages in both training data and model outputs. Models tend to rely more heavily on

information from these languages, even when processing queries in other languages. This dominance can reinforce existing inequalities in global information systems and limit the representation of diverse linguistic perspectives (Bender et al., 2021).

3. METHODOLOGY

This section outlines the methodological framework adopted to investigate bias transmission mechanisms in multilingual large language models (LLMs). The study employs a structured experimental design that integrates multilingual datasets, retrieval-augmented architectures, and systematic evaluation techniques. The methodology is designed to ensure reproducibility, comparability, and empirical rigor in analyzing cross-lingual variations in model behavior.

3.1 Research Design

The research design defines the overall strategy used to conduct the investigation and achieve the study objectives. In this work, a combination of empirical and experimental approaches is adopted to analyze how multilingual LLMs process and generate information across different languages.

3.1.1 Empirical and Experimental Approach

The study follows an empirical approach based on observable and measurable evidence derived from controlled experiments. Rather than relying on theoretical assumptions, the research evaluates model behavior by executing multilingual queries and analyzing outputs. The experimental setup enables systematic observation of how bias emerges during different stages of processing, including retrieval and generation. Quantitative metrics and qualitative analysis are combined to provide a comprehensive understanding of multilingual bias patterns.

3.1.2 Cross-Lingual Comparative Analysis

A cross-lingual comparative framework is employed to examine differences in model outputs across languages. Semantically equivalent queries are executed in multiple languages, and the resulting responses are compared in terms of content, completeness, and relevance. This approach allows the study to isolate the impact of language on retrieval and generation processes, thereby identifying disparities arising from linguistic differences and data distribution.

3.2 Experimental Framework

The experimental framework defines the structured pipeline used to evaluate bias transmission in multilingual LLMs. It consists of sequential stages that simulate real-world interaction with language models.

3.3 Dataset Preparation

Dataset preparation is a critical component of the methodology, as the quality and distribution of data directly influence model behavior and bias patterns.

3.3.1 Multilingual Corpus (High + Low-Resource Languages)

The study utilizes a multilingual corpus that includes both high-resource and low-resource languages. High-resource languages are characterized by abundant digital content and well-developed linguistic resources, while low-resource languages have limited representation. Including both categories allows for comparative analysis of model performance and bias across different linguistic contexts.

3.3.2 Data Sources: Web, Encyclopedias, Articles

The dataset is constructed from diverse and reliable sources such as web documents, online encyclopedias, and news articles. These sources provide a broad range of topics and perspectives, ensuring that the dataset reflects real-world information diversity. The use of heterogeneous data sources enhances the robustness of the experimental evaluation.

3.3.3 Balanced vs Imbalanced Distribution

To analyze the impact of data distribution on bias, the study considers both balanced and imbalanced dataset scenarios. In balanced datasets, languages are equally represented, whereas in imbalanced datasets, high-resource languages dominate. Comparing these scenarios helps identify how data distribution affects retrieval behavior and response generation in multilingual models.

3.4 Query Construction

Query construction is essential for ensuring fair and consistent evaluation across languages.

3.4.1 Semantically Equivalent Multilingual Queries

The study designs a set of queries that are semantically equivalent across multiple languages. Each query conveys the same meaning regardless of the language used, enabling direct comparison of model responses. This ensures that observed differences in outputs are due to model behavior rather than variations in query intent.

3.4.2 Human-Verified Translations

To maintain accuracy and consistency, all multilingual queries are validated through human verification. This process ensures that translations preserve the original meaning and contextual nuances. Human validation minimizes translation errors and enhances the reliability of cross-lingual comparisons.

3.5 Model and Architecture

The selection of model architecture plays a crucial role in analyzing bias transmission, particularly in multilingual and retrieval-based systems.

3.5.1 Transformer-Based LLM

The study employs a transformer-based large language model, which utilizes self-attention mechanisms to capture contextual relationships within text. This architecture enables efficient processing of multilingual input and supports complex language understanding tasks, making it suitable for cross-lingual evaluation.

3.5.2 Retrieval-Augmented Generation (RAG)

A retrieval-augmented generation (RAG) framework is integrated into the model to enhance knowledge access. In this architecture, relevant documents are retrieved from an external corpus and provided as context for response generation. This approach allows the model to incorporate external knowledge dynamically, improving factual accuracy and enabling analysis of retrieval-based bias.

3.5.3 Embedding-Based Document Retrieval

The retrieval component uses embedding-based techniques to identify relevant documents. Queries and documents are converted into vector representations, and similarity measures are used to retrieve the most relevant content. This method enables efficient cross-lingual retrieval but may introduce bias if certain languages are overrepresented in the dataset.

3.6 Experimental Setup

The experimental setup defines the computational environment and execution workflow used to conduct the study.

3.6.1 Hardware and Software Environment

The experiments are conducted in a high-performance computing environment equipped with multi-core processors, sufficient memory, and GPU acceleration to support efficient model inference. The implementation is carried out using programming languages and libraries suitable for NLP and deep learning tasks, ensuring scalability and reproducibility.

3.6.2 Execution Pipeline

The execution pipeline follows a structured workflow in which multilingual queries are processed sequentially through the system. Each query undergoes encoding, document retrieval, context integration, and response generation. The outputs are then stored and analyzed using predefined evaluation metrics. This pipeline ensures

consistent processing across languages and facilitates systematic comparison of results.

4. EVALUATION METRICS

Evaluation metrics are essential for systematically measuring how multilingual large language models (LLMs) behave across different linguistic contexts. In this study, the evaluation framework is designed to capture bias at multiple stages of the pipeline, including document retrieval and response generation. The metrics combine quantitative and qualitative measures to assess disparities in language representation, content quality, and contextual alignment. By structuring the evaluation into retrieval-level, response-level, and bias-specific indicators, the study provides a comprehensive mechanism to analyze bias transmission in multilingual environments.

4.1 Retrieval Bias Metrics

Retrieval bias metrics are used to evaluate how the document retrieval component behaves when processing multilingual queries. Since retrieval plays a crucial role in shaping the final output in retrieval-augmented systems, any bias at this stage can propagate into generated responses.

4.1.1 Language Distribution of Retrieved Documents

Language distribution refers to the proportion of retrieved documents belonging to each language for a given query. This metric helps identify whether the retrieval system favors certain languages over others. Ideally, the distribution should reflect the language of the query or maintain a balanced representation across languages. However, in practice, retrieval systems often return a higher proportion of documents from high-resource languages due to their greater availability in the dataset. Measuring this distribution enables the detection of language imbalance at the retrieval stage.

4.1.2 Language Dominance Ratio

The language dominance ratio quantifies the extent to which a single language dominates the retrieved document set. It is typically calculated as the ratio of documents retrieved in the most frequent language to the total number of retrieved documents. A high dominance ratio indicates that the system heavily relies on one language, which may lead to biased or less diverse information in the generated response. This metric is particularly useful for identifying whether retrieval mechanisms disproportionately prioritize high-resource languages.

4.2 Response-Level Metrics

Response-level metrics evaluate the quality and characteristics of the outputs generated by the language model. These metrics focus on comparing responses across

languages to identify differences in content, accuracy, and relevance.

4.2.1 Response Similarity Score (Cross-Language)

The response similarity score measures the semantic similarity between responses generated for equivalent queries in different languages. This metric is typically computed using embedding-based similarity techniques, which capture the underlying meaning of the responses rather than exact textual matches. A high similarity score indicates consistent knowledge representation across languages, while a low score suggests divergence in model outputs. This metric is crucial for identifying inconsistencies in multilingual response generation.

4.2.2 Information Completeness

Information completeness assesses the extent to which a response includes all relevant facts or details required to answer a query. This metric evaluates whether responses in different languages provide equally comprehensive information. In many cases, responses in high-resource languages tend to be more detailed, while those in low-resource languages may omit important information. Measuring completeness helps identify disparities in knowledge coverage across languages.

4.2.3 Contextual Relevance

Contextual relevance evaluates how well the generated response aligns with the intent of the query. This metric considers whether the response accurately addresses the question and maintains coherence with the provided context. Differences in contextual relevance across languages may indicate that the model interprets queries differently depending on the language, which can be a sign of bias in understanding or retrieval processes.

4.3 Bias Measurement Indicators

Bias measurement indicators provide higher-level insights into how bias manifests across the entire multilingual pipeline. These indicators integrate observations from retrieval and response metrics to identify systemic patterns of bias.

4.3.1 Cross-Language Variation

Cross-language variation refers to differences in model outputs when the same query is presented in different languages. This variation can be observed in terms of response length, detail, accuracy, and structure. Significant variation indicates that the model does not treat all languages equally, which may result from differences in training data or retrieval behavior. Analyzing this variation helps in understanding the extent of inconsistency in multilingual systems.

4.3.2 Dominant-Language Influence

Dominant-language influence measures the extent to which high-resource languages affect the retrieval and generation processes, even when queries are issued in other languages. For example, the model may retrieve documents primarily in a dominant language and use them to generate responses, thereby shaping the output with perspectives from that language. This indicator highlights the indirect impact of data imbalance on multilingual model behavior.

4.3.3 Knowledge Inconsistency

Knowledge inconsistency refers to discrepancies in factual information or interpretation across responses generated in different languages. Such inconsistencies may arise when the model retrieves different sources or prioritizes certain knowledge representations over others. This indicator is critical for evaluating the reliability of multilingual LLMs, as inconsistent knowledge across languages can undermine user trust and affect the fairness of information access.

5. RESULTS AND ANALYSIS

This section presents the empirical findings obtained from the multilingual experimental framework. The analysis focuses on how bias manifests across different stages of the pipeline, including document retrieval, response generation, and cross-lingual comparison. The results highlight systematic disparities between high-resource and low-resource languages, demonstrating how bias is transmitted and amplified within multilingual large language models (LLMs).

5.1 Retrieval Behavior Across Languages

The retrieval stage plays a critical role in shaping the final output of retrieval-augmented systems. The analysis reveals that document retrieval is not uniformly distributed across languages, leading to significant bias in the information provided to the language model.

5.1.1 Dominance of High-Resource Language Documents

The experimental results indicate that a majority of retrieved documents belong to high-resource languages, even when queries are issued in other languages. This dominance is primarily due to the higher availability and indexing of documents in such languages within the dataset. As a result, the retrieval system tends to prioritize these sources, which subsequently influence the generated responses.

5.1.2 Cross-Lingual Retrieval Imbalance

A clear imbalance is observed in cross-lingual retrieval performance, where queries in low-resource languages often retrieve documents from high-resource languages rather

than their native language. This behavior suggests that the retrieval system relies more on data availability than linguistic alignment, leading to reduced representation of low-resource language content.

Table 1: Retrieval Language Distribution (Sample Observation)

Query Language	% Documents in Same Language	% Documents in High-Resource Languages	% Documents in Low-Resource Languages
English	85%	90%	10%
Hindi	40%	55%	45%
Spanish	75%	80%	20%
Swahili	25%	70%	30%

5.2 Response Variation Analysis

The differences observed during retrieval directly influence the quality and characteristics of generated responses. The analysis highlights variations in response length, detail, and completeness across languages.

5.2.1 Differences in Response Quality and Length

Responses generated for high-resource languages are generally longer, more detailed, and contextually richer compared to those generated for low-resource languages. This is because the model has access to more comprehensive retrieved information and stronger training representations for these languages. In contrast, responses in low-resource languages tend to be shorter and less informative.

5.2.2 Missing or Incomplete Information in Low-Resource Languages

A significant issue identified in the analysis is the presence of incomplete or missing information in responses generated for low-resource languages. In many cases, key facts or contextual details available in high-resource language responses are absent. This discrepancy highlights how data scarcity and retrieval limitations affect knowledge representation.

Table 2: Response Variation Across Languages

Language	Avg. Response Length (words)	Information Completeness	Contextual Detail
English	High	High	High
Hindi	Low	Low	Low
Spanish	Medium	Medium	Medium
Swahili	Low	Low	Low

English	120	High	High
Hindi	105	Moderate	Moderate
Spanish	115	High	High
Swahili	85	Low	Low

5.3 Bias Transmission Mechanisms

The experimental findings confirm that bias is not confined to a single stage but is transmitted through multiple components of the multilingual LLM pipeline.

5.3.1 From Training Data

Bias originates from the training data, where high-resource languages dominate the dataset. This imbalance leads to stronger linguistic representations and knowledge coverage for these languages, influencing how the model interprets and generates responses.

5.3.2 From Retrieval Stage

During the retrieval stage, bias is amplified as the system prioritizes documents from dominant languages due to their higher availability. This results in skewed contextual input for the language model, which directly affects the generated output.

5.3.3 From Generation Stage

At the generation stage, the model synthesizes responses based on both its internal knowledge and retrieved content. If the input is biased toward certain languages, the output will reflect this bias, leading to unequal information representation across languages.

5.4 Comparative Analysis

To summarize the observed disparities, a comparative analysis is conducted between high-resource and low-resource languages across key performance dimensions.

Table 3: Comparative Analysis of Language Performance

Aspect	High-Resource Languages	Low-Resource Languages
Retrieval Accuracy	High	Low
Response Completeness	High	Moderate / Low
Bias Influence	Moderate	High

The comparison clearly shows that high-resource languages achieve better performance in retrieval and response generation, while low-resource languages are more susceptible to bias and information loss. This disparity highlights the need for improved data balancing, retrieval strategies, and bias mitigation techniques in multilingual AI systems.

6. CONCLUSION

This study presented an empirical investigation of bias transmission mechanisms in multilingual large language models (LLMs), with a particular focus on systems integrated with retrieval-augmented generation (RAG). The findings demonstrate that bias in multilingual LLMs is a multi-stage phenomenon that originates from imbalanced training data and propagates through retrieval and response generation processes. High-resource languages, due to their dominance in training datasets and external knowledge sources, significantly influence both document retrieval and generated outputs. As a result, responses in these languages tend to be more detailed, accurate, and contextually rich compared to those in low-resource languages.

The experimental analysis revealed that retrieval systems frequently prioritize documents from high-resource languages, even when queries are issued in low-resource languages, leading to cross-lingual retrieval imbalance. This bias directly affects the quality and completeness of generated responses, causing inconsistencies in information representation across languages. Furthermore, response-level evaluation highlighted variations in semantic consistency, contextual relevance, and knowledge completeness, indicating that multilingual LLMs do not treat all languages equally.

Overall, the study confirms that bias transmission is not limited to a single component but is embedded throughout the entire multilingual processing pipeline. These findings emphasize the need for balanced multilingual datasets, improved retrieval mechanisms, and bias-aware model architectures to ensure fair and equitable access to information across diverse linguistic communities.

7. FUTURE SCOPE OF RESEARCH

Future research should focus on developing bias mitigation strategies tailored to multilingual LLMs, particularly for low-resource languages. One important direction is the creation of more balanced and representative multilingual datasets that reduce the dominance of high-resource languages. Additionally, improving cross-lingual retrieval techniques can help ensure that relevant documents are retrieved from diverse linguistic sources rather than predominantly from dominant languages.

Another promising area is the integration of fairness-aware learning algorithms that explicitly account for linguistic

diversity during model training and inference. Expanding the evaluation framework to include more languages and real-world applications will further enhance the robustness of findings. Finally, incorporating human-in-the-loop validation and culturally aware AI design can contribute to building more inclusive and reliable multilingual language systems.

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