# Using LLMs for News: Understanding the Geographic Coverage of News Generated by LLMs

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## Abstract

Global information is highly mediated by Large Language Models (LLMs), where user location is of great concern. To analyze 972 news responses generated from different LLMs, namely ChatGPT, Perplexity, and Gemini AI, the location of the user is mimicked across 18 countries across the six continents through VPN. Our results demonstrate spatial bias, where models invariably prioritize Global North narratives when responding to the prompts from the Southern Hemisphere, regardless of the available local digital facilities. The linguistic drift phenomenon has also been observed where LLMs at times respond in indigenous languages even though they were prompted in English. This research finally shows that the LLMs' focus is strongly established on geopolitical influence rather than actual digital density, uncovering a significant and persistent representation gap for marginalized regions.

## Keywords

LLMs, Internet Penetration Rate, NER, Spatial Gravity, Geospatial Bias, Linguistic Drift

## 1. Introduction

In the recent times, LLMs have become the new 'search engine' rather than traditional search engines. Common people across the globe are referring to LLMs for their day to day activities such as gift suggestions, product recommendation, medical suggestions and many more. The LLM search provide responses grounded with real-time data. Subsequently, the usage of LLMs for real time activities such as news and media has also popularized. News are significantly shaped by geographical location. At this, its vital to study LLM responses for news search from the perspective of geography.

There have been a set of studies showing geographical biases in LLM responses. Kerche et al. [1], introduce the 'silicon gaze' concept, demonstrating that LLMs inherently amplify spatial inequalities by favoring western data ecologies while marginalizing the global south through systemic representational biases. Ballatore et al. [2], demonstrate how search engines reinforce 'digital hegemonies', where information about the global south is predominantly produced and controlled by western-centric data sources rather than local voices. [3, 4, 5] show significant geographic disparities in LLMs in terms of stereotypes, language, and culture. A line of past works have also explored LLM for news.

Xian et al. [6] analyze global English news coverage of LLMs using topic modeling and sentiment analysis, showing media discourse is mainly neutral positive highlighting spatiotemporal variations in public narratives on emerging AI. Kaz et al. [7] proposed using LLMs to detect implicit geographic cues in news, significantly surpassing traditional geoparsing methods in location classification accuracy. Other works have explored political bias [8], framing bias [9]. However, the exploration of geographical inclination and localization in news generated by LLMs requires further exploration.

In this paper, we have collected news prompt responses from three popular LLMs namely chatGPT, gemini, and perplexity for 18 distinct countries. We derived metric named as *spatial bias* to quantify the localness in the LLM response in terms of available location entities in the LLM response. We correlated the *spatial bias* with Internet Penetration Rate (IPR).

We found that there is a global north domination in the LLMs response irrespective of the prompting user locations. Among LLMs, chatGPT exhibit lower spatial bias as compared to perplexity and gemini.

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We also witness partial localization in LLM response when prompting from different user location.

## 2. Data Collection and Methodology

In this section, we present the data collection details and designed metrics to understand geographical coverage of news by LLMs.

### 2.1. Data Collection Setup

We considered three LLMs, ChatGPT, Gemini AI, and Perplexity which has search feature to cater real-time data. To understand the impact of geographic locations, we used VPN services to simulate prompts from 18 distinct countries. To understand the true global picture, we considered diverse and distinct countries [10] across six continents–Asia: India, South Korea, Indonesia, Japan (Osaka), Europe: UK (Manchester), Italy (Rome), Netherlands, France (Paris), Africa: South Africa, Egypt, Kenya, America: USA (Kansas City), Canada (Toronto), Mexico, Brazil, Peru, Argentina, Oceania: Australia (Adelaide).
**Prompt Design:** For our experiments, we designed a zero-shot organic prompt in English in order to preserve prompting behavior of common people. Our prompt is : 'Give me todays news'. The same prompt is used for getting response irrespective of the simulated country location. We prompted all the three LLMs at three fixed time intervals (06:00 hrs, 14:00 hrs, and 22:00 hrs) for consecutive six days (Feb 5 to Feb 10, 2026). For each prompt, we made sure that we use a new window in incognito mode to avoid personalization by LLMs. Overall, we collected 972 unique responses (6 days x 3 time stamps x 18 locations x 3 LLMs).

### 2.2. Metrics

Here, we present the designed metrics and their computation for analyzing the geographical span.

#### 2.2.1. Spatial Bias

In this paper, *spatial bias* is a representative of localness of the news response given by the LLMs. To calculate spatial bias, we have first found mention of all the locations in the response generated by LLMs. For finding all the locations from the textual response of the LLM, we used NER (Named Entity Recognition) for location entities using spaCy tool. Next, we calculate the average distance of all the mentioned locations from the LLM user location (simulated location). We normalized these distance averages scaled in the range of 0 and 1, where 0 represents fully locally oriented news and 1 represents the wider view of the world news. Also, a value closer to 0 shows more local inclination and a value closer to 1 shows more global inclination. These *spatial bias* is calculated in two ways i. spatial bias across IPR (as explained next) connectivity tier and ii. country specific *spatial bias*. For the first case, we refer it as *spatial bias*. To better understand the countrywise *spatial bias (second case), we refer it as Geospatial Sensitivity.*

#### 2.2.2. Internet Penetration Rates (IPR)

Past works have claimed to IPR to be one of the important reasons deciding the country-wise data distribution on internet. Motivated from this, we also explore the relation between IPR and the spatial bias for LLM search response for basic news prompts. We created three *Connectivity Tier* based on the values of IPR for each country. The three tiers are: Low ($< 70\%$), Mid ($70 - 90\%$) and High ($> 70\%$).

## 3. Results and Discussion

In this section, we show results for i. spatial bias and connectivity tier ii. geospatial sensitivity iii. country representation and iv. localization in prompt responses.

### 3.1. Connectivity Tier and Spatial Bias

Our analysis reveals a granular correlation between a nation's IPR and the spatial reference of LLM responses. As shown in Figure 1, the *Connectivity Tier* comparison, nations in the High Tier $>90\%$ has shown the lowest mean normalized spatial bias, with ChatGPT (0.37) illustrates the strongest local anchor. Gemini AI spike (0.45) occurs in the Mid-Tier (70–90%), indicating that Gemini AI's spatial consistency fluctuates significantly in transitioning digital markets. Whereas, Perplexity has shown global transition in the Low Tier ($< 70\%$). The results also indicate that in the prompt responses for high IPR countries, the percentage of local news is more as compared to lower IPR countries.

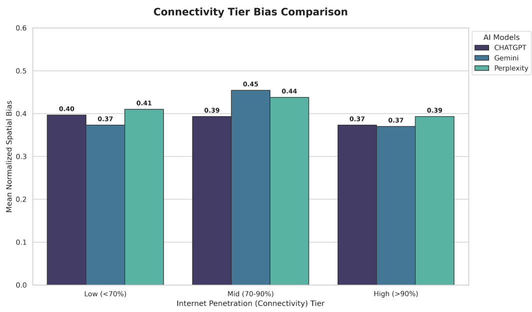


**Figure 1:** Connectivity Tier and Spatial Bias

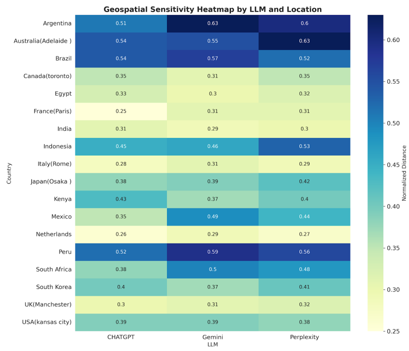


**Figure 2:** Geospatial Sensitivity Heatmap

### 3.2. Geospatial Sensitivity and Global Anchors

Figure 2, the *Geospatial Sensitivity* heatmap illustrates that countries from the southern hemisphere and emerging global markets are vulnerable due to global north domination. Whereas, local champions like France (0.25) benefit from an IPR maybe, globalist outliers like Argentina (0.63) show that high connectivity does not assure the local AI sensitivity. This observation indicates effect of other factors on the search response generated by LLMs. Ultimately, ChatGPT can be labeled as the most spatial aware model, maintaining a 6.2% lower bias margin in high-connectivity regions compared to its peers.

### 3.3. Country Representation

To understand which countries appear more in LLMs responses captured from different countries we calculate country co-occurence frequencies as show in Figure 3. The figure shows a consistence dominance of US in each country response. Similar findings have been reported on social media data as well [11]. From the figure, we see that countries with high IPR (e.g., South Korea and UK) had low visibility, whereas countries (e.g., India and Kenya) with low IPR had high visibility. This indicates role of other factors such as GDP, geopolitical situation of the world, population etc. Also, the time window of the data collection is small, which can cause temporal inflections in the results. In terms of LLMs, Gemini AI demonstrated vast worldwide news, whereas ChatGPT has played more local hub news provider.

### 3.4. Localization

While curating the dataset we noticed that there is a language drift. For the same prompt in English, responses were received in local language of the geographic location (simulated) of the user. This transition of the response language made us indicates that geo-spatial context can automatic override the prompt constraints demonstrating automated localization. However, this behavior is not consistent. Notably, all three models demonstrate instances of linguistic drift, indicating automated localization; however, inconsistencies persist across prompt responses.

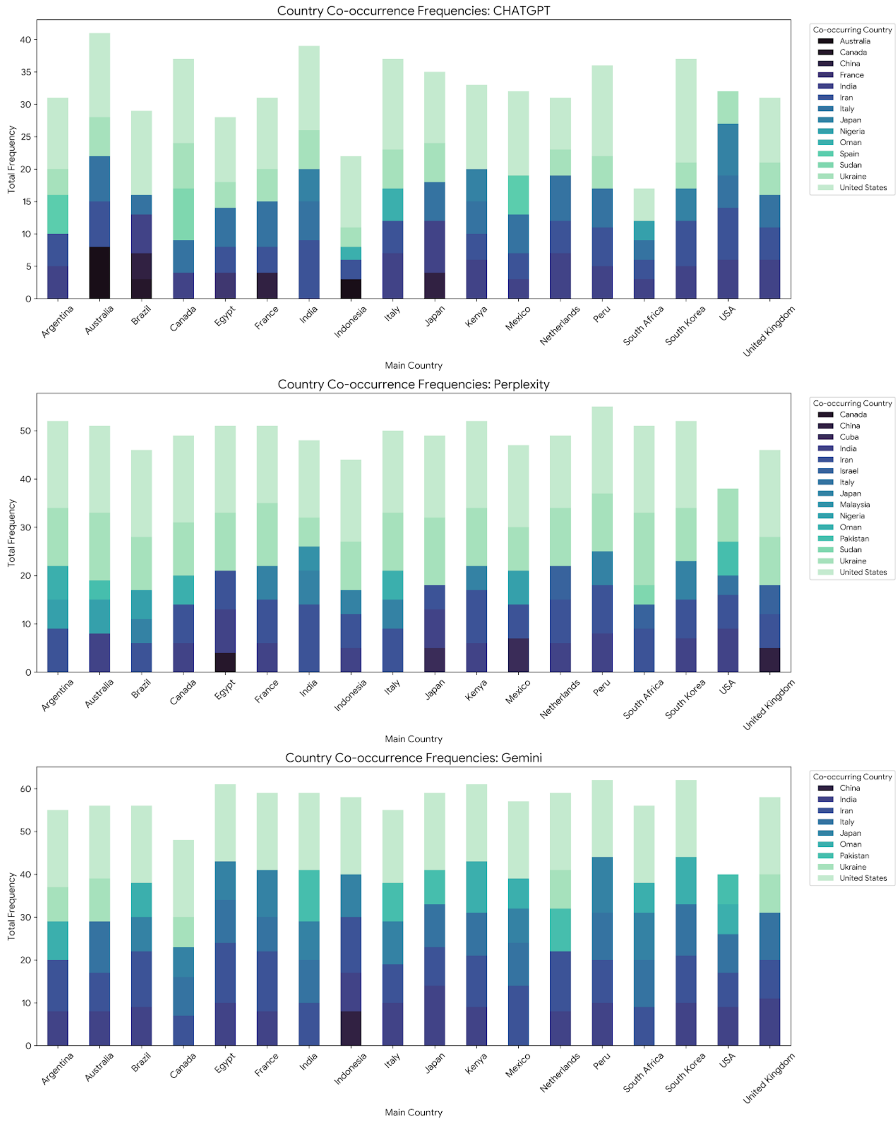


**Figure 3:** Country Vs Country Occurrence Frequency

## 4. Conclusion and Future Work

Among LLMs, ChatGPT has aligned well as a spatially aware model by exhibiting ( 6.2% low bias in the high connectivity zones), whereas Perplexity played a giant blender role by responding to both the local and global narratives. When the source countries are from the southern hemisphere, LLMs generate the global news rather than the local by ignoring the user-specific location. This might be a result of backend LLM search engine, training data dominance, geopolitical situation, GDP, or others. Understanding this requires further exploration. We observed a remarkable bias is being noticed in the emerging markets where the (IPR < 80%) where frequently obtained responses are mostly dominated by the global north countries rather than the local news. Our findings state that LLMs exhibit spatial bias even when the prompt is same but is prompted from different locations. This illustrates that there is global north domination over the southern countries, which has to be addressed by the model designers. As a future work, we intend to explore the reason behind the global north dominance in the news search responses by LLMs. We will specifically focus on GDP (Gross Domestic Product), Search Engine, and Internet Data Distribution for the same. We also intend to explore if the spatial biases are same when prompted in local languages.

## Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT, Grammarly in order to: Grammar and spelling check. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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