THE UNIVERSITY OF CHICAGO

Assessing the Use of Social Media as a Supplementary Tool for Public Opinion Analysis

By

Chris Zhang

June 2024

A paper submitted in partial fulfillment of the requirements for the Master of Arts degree in the Master of Arts in Computational Social Science

Faculty Advisor: Jean Clipperton

Preceptor: Shilin Jia

Abstract

This study investigates social media platforms, specifically Twitter, as a tool for analyzing public opinion Within the U.S. regarding foreign countries. By comparing social media data with Gallup polling data as a benchmark, this research evaluates how well sentiments expressed on Twitter align with those captured through conventional surveys. The analysis spans responses concerning several key global players: China, Russia, North Korea, and Iran, focusing on significant political and social events that might influence public perception.

The findings demonstrate that while traditional polling captures a snapshot of public opinion, social media offers a real-time reflection of public sentiments. Twitter not only mirrors the general direction of public opinion shifts but also reacts more quickly to global events, thus providing nuanced insights into the immediate public discourse. However, it also tends to maintain engagement with topics for longer periods, potentially lagging in recovering from the immediate impacts of significant events compared to traditional methods. This research highlights the complementary nature of social media analysis in public opinion research. It offers valuable insights into both the possibilities and limitations of using digital platforms for sentiment analysis, suggesting that while they should not replace traditional methods, they are instrumental in providing a more comprehensive understanding of public sentiments, especially in response to rapid global developments. This study underscores the importance of integrating various data sources to capture a more holistic view of public opinion dynamics.

Keywords: Public Opinion, Social Media, Twitter, Gallup, Traditional Surveys, China, Russia, North Korea, Iran

1 Introduction

In an era where every tweet and social media post can ripple through public consciousness, understanding the fabric of public opinion has never been more critical. This research dives into a pivotal question: Can social media platforms serve as a supplementary tool for measuring public opinion in the modern era? By focusing on responses from platforms like Twitter against established Gallup surveys, this study explores the divergent landscapes of public sentiment towards global powers such as China, Russia, North Korea, and Iran within the United States context.

The study shows that although the traditional polling method is widely used for public opinion measurement, social media provides new means for public opinion measurement. It not only transitions the measurement from active question answering to the passive collection of public opinion without causing the framing effect to generate bias but also extends the accuracy of the measurement to a certain extent. Traditional measurements are typically done at a fixed point in time, usually one month. This data is used to measure public opinion over an entire year or quarter, ignoring the fluctuations and changes in public opinion that occur in the intervening period. Social media, on the other hand, offers greater flexibility in terms of time scales.

The study contributes to the broader understanding of social media's role in reflecting and shaping public discourse, offering insights into the potential biases and ineffectiveness that may arise in digital versus traditional forms of opinion polling.

2 Literature Review

2.1 The definition of public opinion

Public opinion's definition has been debated, and until now, there is no precise definition. Hans believed that public opinion is "a public communication from citizens to their government" (*Historical Development of Public Opinion* 2024). Another trending perspective is "[Public opinion] is nothing more than the cumulative preferences of individual citizens" (Anstead and O'Loughlin 2015). Noted that the citizens over here are referred to "adults in a particular polity" in this case (Klašnja et al. 2018). Hence, conducting surveys and polls were long regarded as the most effective and accurate strategies. For example, van Klingeren et al. states "there is strong consensus among political scientists and beyond that surveys are an accurate tool to efficiently tap public sentiment" (Klingeren, Trilling, and Möller 2021).

However, with the emergence of social media, people have started to rethink the representatives of traditional surveys. Anstead & O'Loughlin believed that instead of a permanent idea, public opinion's definition should be subject to change. To be more specific, they believe public opinion should include "ongoing product of conversation, embedded in social relationships" (Anstead and O'Loughlin 2015). It implies surveys and polls are no longer satisfied since they are unable to capture active conversations in relationships. It also indicates the necessity of including social media data as a public opinion studying strategy. Specifically, Gao believed that "opinions of Weibo users are representative of public opinion in China to a large extent... public sentiment is a good indicator of public opinion" (Gao, Hua, and Luo 2021).

From a functional point of view, as a tool, public opinion "is mostly concerned with political leaders, group leaders because they try to promote something; Also, based on previous studies, policies were affected by public opinions, [regardless what type of opinions and policies]" (Shapiro 2011). Thus, given social media reflects interactive communication in society and such reflection can be exploited by policymakers, it is reasonable to consider the definition of public opinion in a broader context.

2.2 Social media and traditional polling method

Generally speaking, traditional polling methods for gathering public opinion are susceptible to various influences. According to Ariel Edwards-Levy's analysis of the opinion polls from the 2020 presidential election, the inaccuracy of the results could likely stem from the fact that some segments of the population are more inclined to respond to surveys while others are not. Specifically, she mentioned that "Republicans who were most supportive of Trump were also less likely than other Republicans to answer surveys" (Edwards-Levy Ariel 2021), which might lead to a lower supporting rate towards Trump. Hence, with the dynamic movement of public opinion definitions, the importance of social media became extraordinarily clear. However, social media platforms and using social media as a public opinion evaluation method were criticized for some of their limitations.

Van Klingeren et al. (Klingeren, Trilling, and Möller 2021), argued that Twitter does not have enough representatives to public opinion due to several restrictions. Such an idea was supported by Gabriel Michael and Colin Agur (Michael and Agur 2018). First of all, people who have Twitter access are people who have the intellectual skills to do so. Citizens and the public without access to social media platforms are neglected, including the homeless or elderly. Second, people are selectively exposing themselves to topics they are interested in. They can also set access limitations for certain people. Third, the retweet and reaction mechanism would make some topics seem more important than they are. Fourth, a higher percentage of social media users are male, young people, students, or people highly educated. Overall social media platform is elite-dominated, and it tend to over-represent people with those features. To mitigate the impact of over-representation, van Klingeren et al. collected tweet data using an API to select tweets with at least one keyword and drew a random sample of 3000 posts (Klingeren, Trilling, and Möller 2021). While this method allowed them to obtain a large sample size quickly, it may still suffer from the limitations of Twitter as a representation of the general population. Alternatively, Anstead & O'Loughlin argued that social media, although it is unable to represent the whole population, can provide evidence of "social interaction and conversations rather than simple preference" (Anstead and O'Loughlin 2015). Moreover, social media has a higher engagement rate for young people, which was originally considered a flaw of social media for over-representation. On the other hand, Anstead & O'Loughlin argued that young people were underrepresented in traditional surveys due to age and other factors, so social media actually compensates for the under-representation, which makes it more representative (Anstead and O'Loughlin 2015).

Second, it was also believed that social media public opinion is closely associated with social network structure and online social context (Zhang, Chen, and Rohe 2022). Current studies show that public opinion on social media often exists within echo chambers, where people with similar viewpoints interact without engaging with opposing views. However, discussions that involve differing perspectives can happen early in non-political settings and are more common on some platforms (Barberá et al. 2015). Therefore, instead of relying on comparing social media analysis results with survey-based opinion polls, Zhang et al. utilized a murmuration framework to capture the dynamics and contexts of social media discussions within groups, known as flocks (Zhang, Chen, and Rohe 2022).

Another pending issue of social media platforms is the influence of social media itself on public opinion. Zhan et al. examined the effect of social media on public opinion formation and realized social media has a polarization effect on people's opinions. Specifically, larger network scales tended to yield smaller ratios of uncertain opinions. That means people with medium opinions or uncertain ideas express less when they are in a large social network. They also claim that a large network scale will lead to fewer opinion clusters (Zhan et al., 2019). Similarly, research was conducted by Wu et al. to explore opinion convergence and movements on social media platforms. Specifically, they posit that "individuals are influenced by the tweets around them, and that opinion convergence is a dynamic process through central and peripheral routes of elaboration likelihood" (Wu et al. 2011).

Despite all limitations discovered in social media as a tool, it provides an alternative and inclusive platform for understanding public opinion (Anstead and O'Loughlin 2015). It captures the ongoing conversations and social interactions that shape public sentiment. Besides, social media offers a dynamic view of public opinion, allowing researchers to study the development of opinions over time (Anstead and O'Loughlin 2015). Additionally, it enables the examination of public opinion within specific demographic groups or communities, which is not feasible with traditional surveys (Anstead and O'Loughlin 2015).

In general, social media and public opinion surveys have distinct characteristics in studying public opinion. Specifically, social media provides a dynamic perspective but has a biased user composition and a higher margin of error. Surveys offer lower biases but may be influenced by framing effects. Understanding these distinctions helps in interpreting divergent results and analyzing specific cases of public opinion.

2.3 Social Media Public Analysis Methodology

In the burgeoning field of digital communication, the analysis of public opinion via social media has emerged as a pivotal area of study. Researchers have employed a variety of methodologies to mine and interpret the vast quantities of data generated by platforms such as Twitter and Facebook. Each method provides a unique lens through which to understand the complex tapestry of public sentiment and its impact on societal and political dynamics. Often, these studies correlate social media activity with specific political or societal events, such as those outlined in the Bully Pulpit initiative or similar analyses by Yiwu et al (Wu et al. 2011). The predominant approach to data extraction from social media platforms involves keyword searches and categorizations, enabling the collection of data related to particular topics (Michael and Agur 2018).

Beyond keyword scraping, hashtags have emerged as a potent tool for targeted data collection, offering a practical alternative illustrated by Yiwu et al.'s research into public opinion surrounding the Singapore election (Wu et al. 2011). Furthermore, Y. Zhang et al. introduced an innovative data collection method via a murmuration framework that amalgamates hashtags, Twitter lists, and social network structures to pinpoint tweets for subsequent analysis (Zhang, Chen, and Rohe 2022). This strategy surpasses simple sentiment or topic aggregation, recognizing that public opinions can exhibit strong consistency within certain groups while varying significantly between them.

In terms of analytical focus, research varies considerably. Some studies emphasize the frequency of tweets pertaining to specific opinions, as seen in the Bully Pulpit project, to discern shifts in population groups aligned with particular viewpoints. Another common analytical method involves computing sentiment scores from raw text through various tools such as NLTK or manual computation. Despite sentiment analysis modules' propensity for inaccuracies, Kloumann et al. and Dodds et al. manually curated a list of commonly used words and, with assistance from Amazon's Mechanical Turk, computed sentiment scores on a set scale, potentially enhancing the ability to discern sentiments from text, although introducing the risk of human bias (Dodds et al. 2011).

Other methods were also experimented with to capture the sentiment structure of social media text. Johan Bollen et al. expanded upon the Profile of Mood States (POMS) model, assessing six distinct mood dimensions within texts, potentially reducing human bias while increasing the accuracy of sentiment analysis (Bollen, Mao, and Pepe 2011). Furthermore, Yini Zhang et al. analyzed social media data employing a murmuration framework, eschewing the notion of social media users as a monolith and differentiating the diverse opinions that emerge across the social media spectrum (Zhang, Chen, and Rohe 2022).

Therefore, analyzing public opinion on social media extends beyond the frequency analysis of keywords and hashtags. It involves an understanding of how different types of content—informative and affective—work in tandem to influence collective sentiments. Studies like those by Bollen et al. and Wu et al. underscore the importance of using sophisticated sentiment analysis tools and semantic network analysis to capture the complexity of public opinion as manifested on social media platforms (Bollen, Mao, and Pepe 2011; Wu et al.

2011).

3 Research Significance

Based on the discussions above, including the exploration of the definition of public opinion and the advantages and disadvantages of using social media as a research tool, this study holds significant relevance in exploring the role of modern technology in the field of public opinion research. As traditional polling methods face challenges in maintaining representative samples and high response rates, the potential of social media as a supplementary or alternative source for gauging public sentiment has garnered significant academic and practical interest. This study's comparative analysis between Twitter, a leading social media platform, and Gallup, a standard-bearer in traditional polling, provides valuable insights into the congruence and discrepancies in public opinion measurement across digital and conventional mediums.

By exploring the representation and accuracy of social media-based public opinion in comparison to traditional survey data, this research contributes to the broader understanding of social media's role in reflecting public discourse. Specifically, for policymakers, the findings of this study are instrumental in refining communication strategies and policy formulations. By elucidating the disparities between perceptions captured through traditional polling and those expressed on platforms like Twitter, this research offers a comprehensive view of public sentiment, facilitating more informed governmental decisions, especially in dynamic policy environments. Furthermore, advocacy groups and non-governmental organizations can apply the findings to optimize their advocacy strategies. Understanding the nuances of how social media influences public opinion and the potential misalignment with traditional survey data enables these groups to tailor their communications more effectively, ensuring that their campaigns resonate accurately and compellingly with public sentiments.

Circling back to the research topic, analyzing public opinion towards nations like China, North Korea, Russia, and Iran is crucial due to their significant roles in current global geopolitics. These countries frequently appear at the center of international tensions and conflicts that can have wide-reaching implications. For example, China's emergence as a global superpower involves complex trade relationships and territorial disputes that influence global policymaking. Similarly, North Korea's nuclear ambitions, Russia's active participation in regional conflicts and cyber activities, and Iran's nuclear program and regional influence in the Middle East are pivotal in shaping global strategic decisions. Public sentiment towards these nations can guide governmental foreign policies, impacting bilateral relations, trade agreements, and international security strategies. Understanding public opinion is essential for crafting policies that are responsive to the public's perspective and maintain national and international security.

4 Data

This study evaluates the effectiveness of using social media in public opinion assessment by analyzing two data sources: traditional Gallup census data and Twitter interactions. The Gallup data, collected annually every February, assesses American perceptions of major global threats, including China, Russia, North Korea, and Iran (Gallup 2023). Concurrently, Twitter data comprising 52,821 comments, posts, and replies was gathered through an API

(David 2023) using specific keywords and time constraints. This combination allows for a comprehensive comparison of public sentiment trends over time, bridging traditional and digital platforms.

4.1 Twitter

In the context of this study, both social media data and conventional survey data were analyzed to examine public sentiments toward various nations. The platform of choice for social media data was Twitter. This decision was predicated on the comparative analysis of platform characteristics. Notably, Facebook's tendency to host private content within user-specific networks or groups significantly impedes the accessibility of data for scholarly research without explicit permissions. This presents a substantial barrier to the execution of large-scale data collection initiatives. Furthermore, Reddit, despite its provision of publicly accessible data, organizes content into community-specific forums (subreddits), potentially constricting the diversity of opinions on broader subjects in contrast to the more expansive discourse facilitated by Twitter.

The temporal scope of the research was deliberately set over a period of six years, from 2018 to 2023, to align with the availability of consecutive polling data from Gallup, given that Gallup polling surveys have a missing value in year 2017. The choice of this period also capitalizes on the relevance and timeliness of the data, as more recent data tends to be more accessible and valid for reflecting public opinions. Moreover, a six-year duration is sufficiently extensive to permit the observation of significant shifts in public opinion, thereby facilitating valid comparative analysis between social media and Gallup data.

Data collection was systematically conducted every month, wherein a consistent sample of at least 160 tweet interactions—comprising comments, posts, and replies—was collected for each month from 2018 to 2023. Due to the data loss inherent in filtering and cleaning, the Twitter data collection was conducted in two stages. Initially, 150 tweets per month for each target country were collected. Because Gallup data studies Americans' perceptions of other countries, the Twitter data cleanup step filters out tweets where the user's location is not within the United States. Given the expected reduction in the volume of data after the cleansing process, a follow-up data collection was implemented until the after-cleaning data reached a minimum of 160 tweets per country per month. This two-stage approach ensured adequate data volume for robust analysis. The 150-tweet volume was chosen to balance the computational feasibility of processing, translating, and analyzing tweets, and the budget, ensuring that each month was equally represented and contributed to an overall understanding of public sentiment throughout the year. Consequently, this approach was replicated across the four nations under investigation—China, Russia, North Korea, and Iran—resulting in an accumulation of 12000 - 14000 posts per country, which culminated in a dataset of 52818 tweets.

In the collection of tweets from Twitter for this study, attention was focused on five primary parameters: "date_created", "URL", "full_text", "user_id_str", and "user/location". These parameters correspond to the timestamp of the tweet's creation, the unique URL of the tweet, the complete textual content of the tweet, the unique identifier for the user who posted the tweet, and the location of the user. Subsequent sections of this research will delve into the methodologies and analytical processes applied specifically to the "date_created", "full_text", and "user/location" parameters.

The acquisition of Twitter data for this research was facilitated through the utilization of a third-party Application Programming Interface (API), specifically the Twitter Scraper API available at https://apify.com/microworlds/twitter-scraper (David 2023). This API was instrumental in systematically collecting tweets spanning a period from 2018 to 2023, focusing on four distinct countries. Each query is structured with several key parameters to ensure precise data extraction. Firstly, the period for each query is defined monthly, starting at 00:00 on the first day of the month and ending at 23:59 on the last day. This allows for a comprehensive capture of data within specific monthly intervals. Secondly, queries are designed around country-specific keywords to accurately target relevant tweets. For instance, a query to collect tweets about Russia in January 2018 would use "Russia" and "Russian government" as keywords, with the time parameters set from January 1, 2018, to January 31, 2018. Third, to optimize the relevance and quality of the data retrieved, the 'top' parameter was employed in preference to the 'latest' parameter within the API's querying capabilities. The 'top' parameter is designed to return tweets that most closely align with the specified search keywords, selecting them randomly from the entire pool of available tweets. This approach was adopted to capture the most pertinent and impactful tweets related to the subjects of interest, thereby enhancing the potential insights to be derived from the data.

China	Russia	North Korea	Iran
Chinese Government	Russian Government	North Korean Government	Government of Iran

Table 1: Keywords associated with countries and their governments.

The keywords selected for each search query, as detailed in Table 1, were carefully chosen to not only include the name of the country under investigation but also a compound term combining the country's name with "government". This dual-keyword strategy is crucial for several reasons. Firstly, it aims to capture a broad spectrum of tweets that discuss both the country and its governmental actions, thus providing a comprehensive view of public opinion and discourse on the governance and political dynamics of each country. Such a selection is especially pertinent given the research focus on public sentiment towards these countries, often in the context of viewing them as adversaries, which is primarily influenced by their political actions or leadership. Moreover, using keywords related to the country and its government helps avoid bias that could arise from keywords associated with specific events or possessing inherent positive or negative connotations. The sole exception in keyword selection pertained to Iran, where "Government of Iran" was utilized instead of "Iranian Government" due to its greater prevalence in Twitter searches. In contrast to the keywords for China, Russia, and North Korea, which were selected based on their potential to generate a high volume and broad spectrum of content, the "Government of Iran" keyword showed a lesser frequency and diversity in search results. After determining the keywords, a preliminary search was conducted on Twitter to verify that they yielded valid tweets, further confirming their effectiveness in retrieving relevant and unbiased data.

4.2 Gallup

The selection of Gallup as the source for traditional survey data was predicated on its comprehensive representation of the population, alongside the provision of relevant data on public opinion topics, thereby facilitating an enhanced efficiency for this study. In pursuit of analyzing public sentiment towards four nations, this research utilized data from Gallup's survey entitled "Americans Continue to View China as the U.S.'s Greatest Enemy" (Gallup 2023). Conducted by Gallup annually in February, this survey seeks to elucidate U.S. public opinion on various international actors.

This particular survey was selected as a data source to illuminate perceptions regarding countries such as China, Iran, North Korea, and Russia, given that the survey's inquiries align closely with the methodological framework and objectives of this study. Although initially executed as an open-ended survey, the reported outcomes predominantly emphasize the foremost responses of four countries: China, Iran, North Korea, and Russia, which facilitate the data collection process on Twitter. The raw data from Gallup, spanning from 2001 to 2023, encounters several instances of missing data for the years 2002–2004, 2009–2010, 2013, and 2017. Consequently, this analysis was confined to data from the period 2018–2023, which is devoid of missing entries.

DATE	**% China**	**% Russia**	**% North Korea**	**% Iran**
2014	20	9	16	16
2015	12	18	15	9
2016	12	15	16	14
2017	N/A	N/A	N/A	N/A
2018	11	19	51	7
2019	21	32	14	9
2020	22	23	12	19
2021	45	26	9	4
2022	49	32	6	2
2023	50	32	7	2

Table 2: Gallup research - Which country do you consider to be America's greatest enemy?

5 Method

For the methodologies employed, the Twitter dataset is rigorously pre-processed to ensure accuracy and uniformity. This involves cleaning and standardizing the data by removing duplicates, filtering out irrelevant content, translating non-English tweets, and excluding users not located in the US. Initially, sentiment analysis is conducted using the Natural Language Toolkit (NLTK) SentimentIntensityAnalyzer (Team 2023) to assign sentiment scores, categorizing tweets as either positive or negative. This analysis serves to quantitatively assess public opinion, where I compute the percentage of negative tweets each month based on these sentiment scores. This step is crucial as it allows for a direct comparison with results from Gallup surveys, aligning social media sentiment trends with established polling data.

Following the sentiment analysis, the research design includes a focused examination of public discourse related to specific social events in each country. Using a pre-trained BERT model (*GroNLP/hateBERT · Hugging Face* 2024), topic modeling is applied to explore how discourses and sentiments shift before and after significant events. This method provides a detailed view of the dynamics of public opinion over time, offering a nuanced understanding of how societal events influence public perceptions and shape social media discourse. This comprehensive approach not only aligns social media data with traditional Gallup data but also delves deeper into specific events to track fluctuations in public discourse, enriching the analysis of public opinion formation.

	China	Russia	Iran	North Korea
Beginning Tweets	18002	17165	19408	15023
Duplicate Tweets and less than 5 character removal	497	2234	805	499
Not Within US removal	2873	2296	5084	2492
End Tweets	14632	12635	13519	12032

Table 3: Tweet Pre-Processing Statistics by Country

5.1 Pre-Processing

Before analyzing the social media data, a meticulous preprocessing of the Twitter dataset was conducted to streamline the analysis process. This involved several key steps. Initially, data from each country were merged into a unified data frame, providing a cohesive dataset. Timestamps of tweets were then parsed into year and month categories for future aggregation. To address the linguistic variety in the Twitter dataset, a translation process was integrated to convert non-English tweets to English, standardizing the dataset for consistent analysis. The preprocessing also entailed cleaning procedures using the Natural Language Toolkit (NLTK) for text processing. These procedures focused on removing duplicate tweets, tweets with missing values, irrelevant stop words, and HTTP links. In pursuit of analytical accuracy, tweets containing fewer than 5 characters were filtered out, under the assumption that they lacked enough content for reliable sentiment analysis. Additionally, a filtering process was applied to exclude all tweets from users not located in the United States, since the Gallup poll primarily targets U.S. citizens. After the initial cleaning, any country with fewer than 150 tweets per month underwent a recollection process. This involved gathering batches of 100 tweets to ensure a sufficient monthly total and to minimize discrepancies in tweet volumes across countries. As illustrated in Table 3, it shows the total number of original tweets, the number of duplicate tweets and those with less than 5 characters, tweets not originating within the US, and the final count of valid tweets after removing these tweets. The pre-processing process involved removing tweets due to inadequate length and duplications. Despite the exclusion of these tweets, the reductions are within a reasonable range, ensuring no bias in our analysis. Specifically, of the original dataset, approximately 5% were filtered out overall. This leaves a robust dataset that is both sizable and varied enough to maintain the integrity and representativeness of the analysis.

5.2 Sentiment Analysis

For the sentiment analysis component of this study, the Natural Language Toolkit (NLTK) SentimentIntensityAnalyzer (*NLTK :: Natural Language Toolkit* 2024)was utilized to calculate a sentiment score for each post. The NLTK library's SentimentIntensityAnalyzer function generates compound sentiment scores ranging from -1 to 1, facilitating the delineation of tweets into categories of positive and negative attitudes based on their sentiment scores. According to the NLTK and generalized sentiment score division rules, a sentiment score greater than or equal to 0.05 is classified as positive sentiment, less than or equal to -0.05 is classified as negative, and a sentiment score greater than -0.05 and less than 0.05 is classified as neutral (Hutto 2024).In the current study, I followed this threshold as the dividing line between positive and negative. That is, when calculating the number of negative sentiment tweets in the dataset, their number is determined by the number of tweets with a sentiment score less than -0.05. However, given the inconsistency between actual behavior and the sentiment score expressed, I also conducted a preliminary exam before determining the threshold. By adjusting the number of thresholds to simulate the results in different scenarios, it was eventually found that the results in the case of -0.05 as the negative sentiment threshold were closest to the results of Gallup's data.

To align the social media data with the Gallup survey and to analyze public sentiment trends over time, the percentage of negative tweets per month was computed for the respective countries as Sentiment Index. This calculation serves as a means to assess the variability and intensity of public sentiment, offering insights into the fluctuations in public opinion over the examined period. Central to this method is the utilization of the Sentiment Index as shown below. This approach is justified as Gallup's data measures the percentage of U.S. residents who view certain countries as adversaries. Similarly, I analyzed social media data to calculate the percentage of negative tweets regarding each country, relative to the total number of tweets collected.

$$\textbf{Sentiment Index} = \frac{\textbf{Number of Negative Sentiment Comments}}{\textbf{Total Comments within a year}}$$

It's important to note that the Gallup survey data, which is collected every February, captures a snapshot of public opinion at that specific point in time rather than tracking changes over an extended period. This characteristic influenced the methodology of the initial sentiment change comparison in this study. To align the analysis with the timing of the Gallup data collection, only the Twitter data from February of each year was utilized for initial general trend comparison. This approach ensures that the sentiment analysis from social media corresponds temporally with the Gallup data, providing a more accurate comparison of public opinion at similar times.

5.3 Topic Modeling

In my research, I employed the BERT (Bidirectional Encoder Representations from Transformers) model, specifically the *cardiffnlp/twitter-roberta-base-sentiment-latest*, to perform topic modeling on a dataset of translated tweets (*GroNLP/hateBERT · Hugging Face* 2024). The BERT model provides better vector representations of sentences than those obtained with BOW (renato 2021). And the pre-trained BERT model also could perform wide range of tasks without substantial modifications (Devlin et al. 2019). To identify distinct topics within the data, I applied clustering algorithms to these embeddings and used the elbow method to determine the optimal number of clusters by identifying the point where the within-cluster sum of squares' improvement became marginal. For each cluster, I extracted and displayed representative tweets, which provided insights into the thematic content of each group, demonstrating the capability of deep learning embeddings to reveal complex themes in textual data efficiently.

The *cardiffnlp/twitter-roberta-base-sentiment-latest* model is particularly effective for Twitter data analysis due to its specialized training on Twitter-specific content, which includes the platform's unique linguistic features such as hashtags and informal language. Leveraging the RoBERTa architecture, it offers enhancements over the original BERT model by optimizing training conditions and focusing on more nuanced language understanding. This specialization ensures superior accuracy in processing and analyzing tweets, making it an excellent tool for real-time sentiment analysis and understanding Twitter dynamics.

Considering the dynamic nature of public opinion, influenced by significant social and political events, I explored how social media-based public opinion responds to these occurrences compared to traditional polling methods. To facilitate this comparison, I manually selected four major social events in each of the four countries as shown in the following table. To analyze public opinion dynamics around major social events, I modeled topics on social media data for five months before and after the start of each event (excluding the month in which the event occurred). This approach helps distinguish anticipatory and reactionary sentiments, revealing how public discourse evolves.

China	**Russia**	**North Korea**	**Iran**
COVID-19 Outbreak in China	Invasion of Ukraine	President Trump met with Kim	Iranian protests
2019-11	2022-02	2019-07	2019-11

Table 4: Social events associated with countries

6 Results

The results section of the thesis delves into public sentiment towards four countries—China, Russia, North Korea, and Iran—analyzed across three main categories: sentiment fluctuation comparisons between Gallup and Twitter, sentiment distribution during months with notable inconsistencies, and topic modeling outcomes.

For China, the comparison of sentiment fluctuations showed that Twitter sentiments were highly variable and reactive to current events, contrasting with the Gallup data, which displayed a steady increase in negative sentiment from 2018 to 2023. Notably, during specific months in 2021 and 2022, Twitter showed periods of unexpected positivity, starkly contrasting with the consistently negative trends in Gallup results. Topic modeling for these years indicated that discussions often centered around political events and government actions, and there were instances of misclassification of tweets with negative sentiments that led to positive sentiment spikes, contradicting the overall negative trend.

In the analysis of Iran, Twitter displayed dramatic sentiment fluctuations, particularly in response to political crises, diverging from the relatively stable trends observed in Gallup data. Both platforms indicated an overall increase followed by a decrease in sentiment from 2018 to 2023. However, in 2022 and 2023, Twitter sentiment distributions notably shifted towards negative views. Topic modeling showed frequent discussions on international sanctions and diplomatic negotiations, significantly impacting the public sentiment reflected on social media, with misclassifications also noted in this analysis.

For North Korea, Twitter sentiment was markedly volatile, contrasting with the more stable Gallup responses, which portrayed a relatively constant public view from 2019 to 2023. Although both Gallup and Twitter suggested a gradual positive sentiment trend from 2019 to 2022, Twitter data highlighted sharp public reactions to North Korea's actions, especially in 2019 and 2023. The predominant discussions revolved around military activities, significantly influencing public sentiment.

Regarding Russia, sentiment fluctuations on Twitter were less pronounced but similarly reactive to significant news events, unlike the more consistent Gallup data. Particularly in 2019 and 2021, Twitter showed rapid shifts in public sentiment during major geopolitical events involving Russia. Topic modeling indicated that the focus was on international diplomacy and conflicts, which temporarily influenced sentiment on social media.

Overall, these findings demonstrate the dynamic and reactive nature of social media in capturing public sentiment, contrasting with the more stable and consistent data from traditional polling methods like Gallup. This comparative analysis highlights the complexities and challenges of accurately gauging public opinion in the digital era.

6.1 General Sentiment Analysis

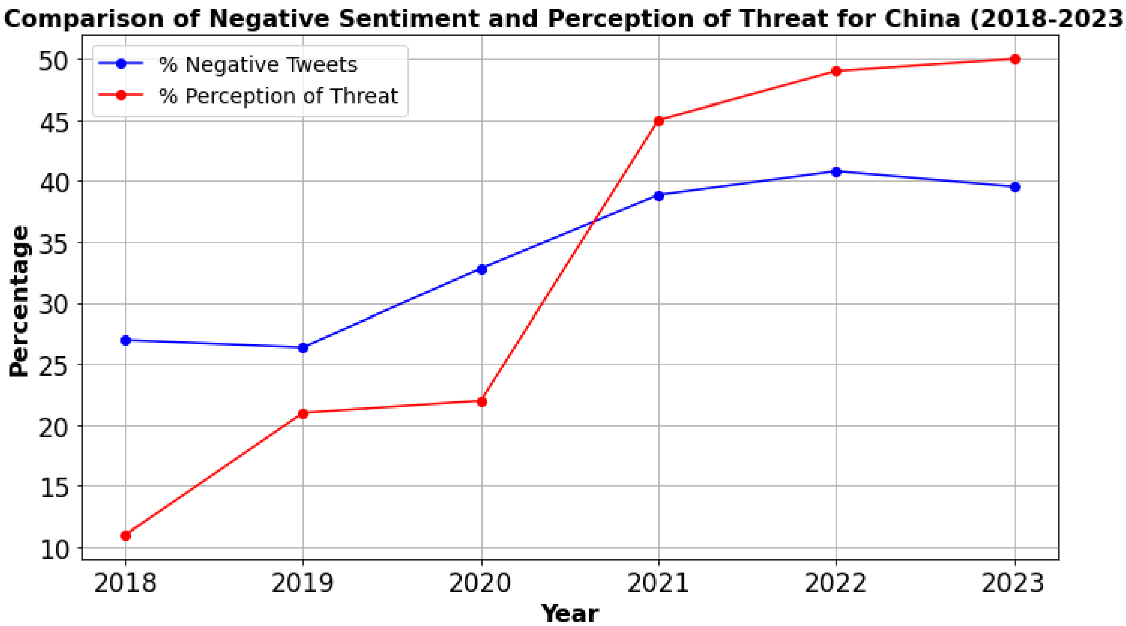

Figure 1: China Sentiment

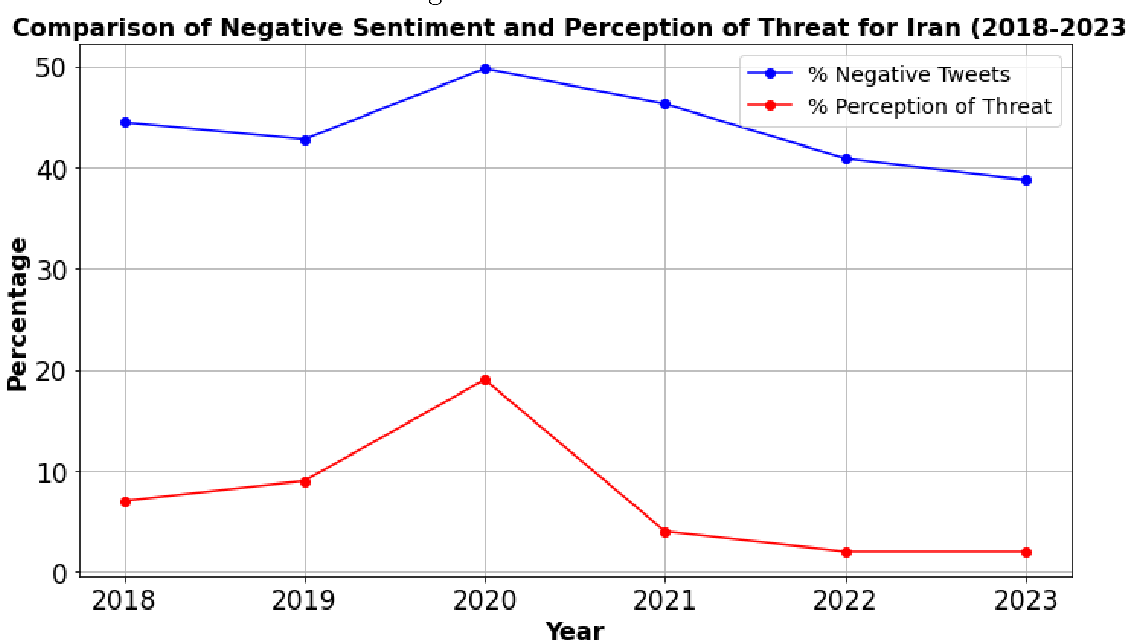

Figure 2: Russia Sentiment

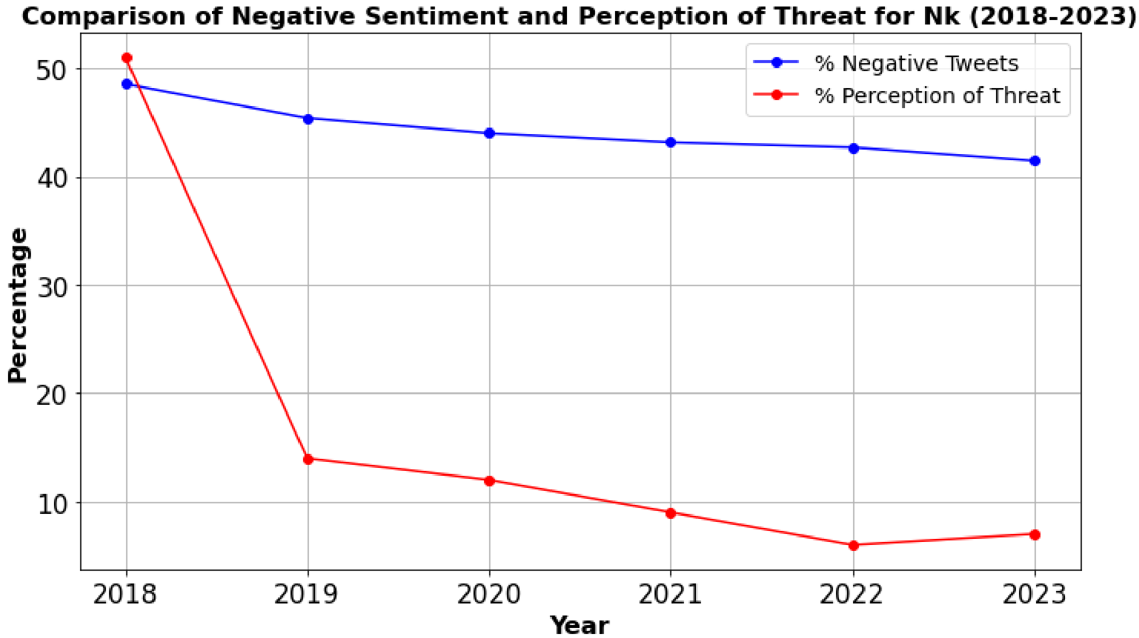

Figure 3: North Korea Sentiment

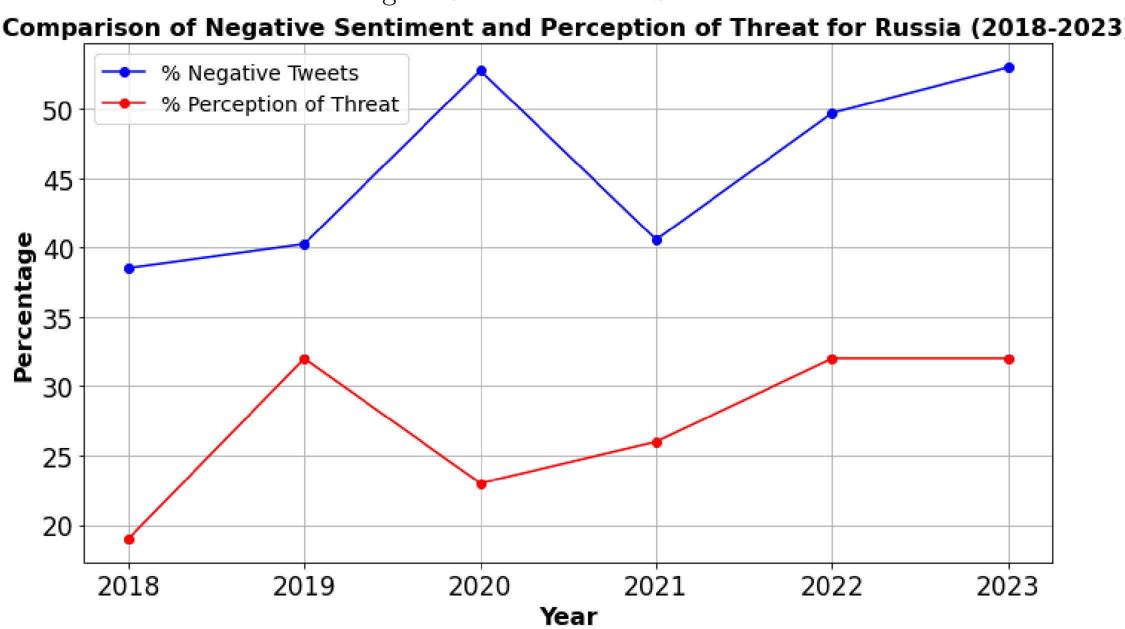

Figure 4: Russia Sentiment

In this section of my thesis, I utilized Twitter data from February of each year to compute the percentage of negative tweets for specific countries and compared these results with Gallup polling outcomes. The analysis, as depicted in the accompanying figures, shows that both Gallup and Twitter data exhibit high similarities in tracking public opinion trends (increasing or decreasing) across the four examined countries, albeit with some minor discrepancies and intersections. This indicates that tweet sentiment movements are highly correlated with how people perceive different countries as U.S. enemies.The similarities in overall trends between Twitter and Gallup data underscore that social media can effectively serve as a supplementary tool for gauging public opinion. This alignment proves that social media data is capable of predicting general public sentiment trends comparably to traditional polling methods.

However, it is important to note two critical considerations. Firstly, as shown in the figures, Twitter tends to predict a higher percentage of negative tweets compared to the perception of threat measured by Gallup polls. This discrepancy arises due to the different methods each platform uses to gauge public opinion. The methodology for predicting trends from social media assumes that fluctuations in public opinion correlate with the percentage of negative tweets. This is analogous to Gallup data, which measures the percentage of people who view certain countries as the United States' greatest enemies—a potential indicator of public sentiment towards those nations. Under specific circumstances, this correlation may not hold as robustly, suggesting that the reliability of social media in evaluating general public opinion on this matter might require further refinement.

Besides the overarching similarities, some minor discrepancies between Twitter and Gallup data were noted during the analysis. For instance, Twitter data showed an obvious increase in negative sentiment towards China following the COVID-19 outbreak in November 2019, while Gallup data depicted a relatively stable sentiment trend during the same period. Similarly, Twitter data reflected a significant rise in negativity towards Russia after the invasion of Ukraine, a change not observed in Gallup data, which remained unchanged. For Iran, Twitter data demonstrated a gradual recovery of positive sentiments after the 2019-2020 Iranian protests, contrasting with Gallup data, which showed a sharper reduction in negativity held by U.S. citizens towards Iran. Additionally, Gallup data indicated a steep decrease in negative sentiment towards North Korea, a trend that appeared smoother in the Twitter data. These discrepancies highlight the nuanced differences in how social media and traditional polling capture and reflect shifts in public opinion under varying geopolitical circumstances.

The discrepancies in sentiment changes between Twitter and Gallup data suggest that, in comparison, Gallup data might exhibit more volatility and a time lag in responding to social eventswhile Twitter data shows relatively smoother movements. For example, the decrease in the Gallup index for North Korea from 2018 to 2019 is around 70%, while the decrease observed in Twitter data is much smaller, accounting for less than 10%. While Gallup trends often show more dramatic shifts, they also tend to react more slowly to social events on a temporal scale. This pattern indicates that traditional polling methods may amplify the volume of sentiment changes when they do register, yet do not capture the immediate fluctuations as swiftly as social media platforms like Twitter, which continuously reflect real-time public opinions and reactions to global events. To understand the discrepancies between social media-based public opinion and Gallup data, I conducted additional monthly sentiment analysis and topic modeling for each country before and after major social events. This analysis aimed to explore the dynamics of public sentiment, revealing how specific events influence opinions over time and highlighting the immediacy and evolution of reactions on social media compared to traditional polling methods.

6.2 Countries Analysis

6.2.1 China

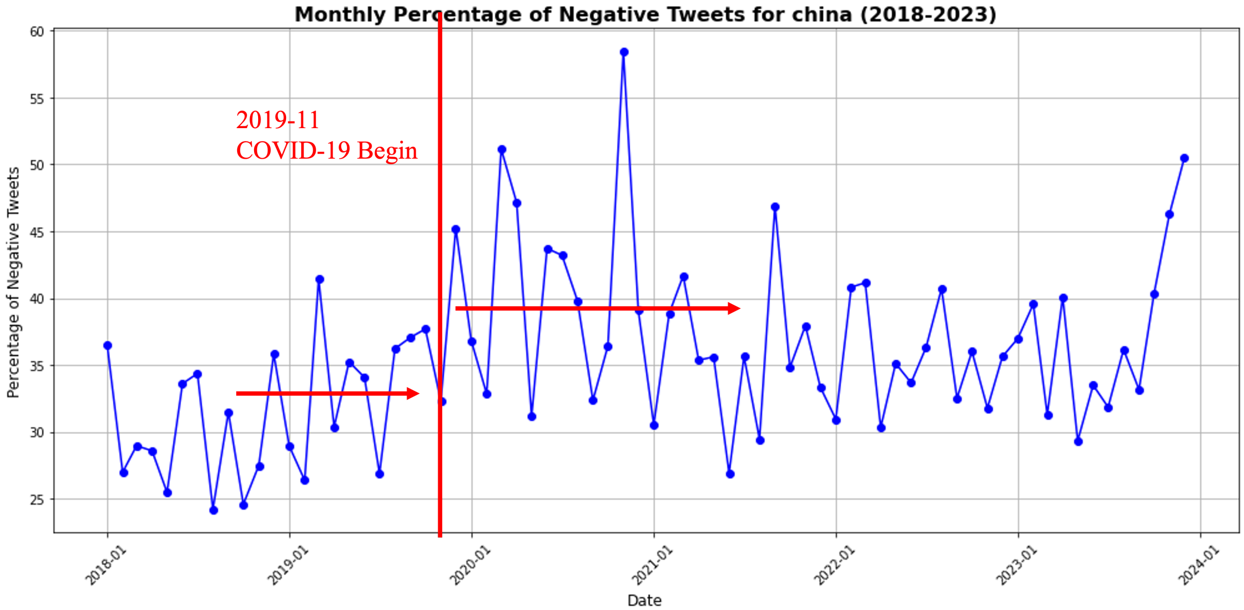

Figure 5: Sentiment Analysis for China

A closer examination of the sentiment index for China reveals that, contrary to the apparent increasing trend in negative sentiment predicted by Gallup, social media-based sentiment indicates a relatively stable movement over time. While there is a noticeable increase, it is not as dramatic as shown in Gallup's results. This discrepancy could stem from the fact that Gallup data captures public opinion only in a specific month each year, potentially lacking representativeness. For instance, if the Gallup polling were conducted in March instead of February, the results might differ, highlighting how the timing of data collection can significantly influence the perceived trends in public sentiment.

The change in the percentage of negative tweets for China, as depicted in Figure 10, shows a noticeable increase in negative sentiments immediately following the COVID-19 outbreak in November 2019. Social media data captured this shift, with the average percentage of negative tweets rising from around 32% to 39%. This difference was distinctly marked post-November 2019. In contrast, Gallup data displayed relatively stable changes in public sentiment towards China from 2019 to 2020. Considering that Gallup's polling was conducted in February 2020, it is possible that the influence of such a significant social event as the COVID-19 outbreak had not yet been reflected in their survey results. That is to say, the emergence of the first COVID-19 case in Wuhan, China, did not immediately translate into a significant shift in public perception of China as an enemy. The first COVID-19 death in the United States occurred in February 2020, closely aligning with when Gallup's polling was conducted. By March 15, 2020, the U.S. State Department had issued a health advisory recommending against travel, but it is possible that the full impact of these developments had not yet permeated the public consciousness. Therefore, participants in the February polling might not have been mentally or behaviorally influenced by the unfolding events, suggesting a delay in the reflection of such major social events in traditional polling data.

However, in contrast, social media, with its characteristic of providing the latest news and facilitating global discussions, is more susceptible to immediate reactions to news and social events. This responsiveness allows sentiments on platforms like Twitter to reflect changes more rapidly than traditional polling. Consequently, discourses regarding COVID-19 on social media might have indicated negative sentiments towards China earlier than detected by Gallup polls. This illustrates the capacity of social media to serve as a real-time barometer for public opinion, capturing shifts in sentiment that precede those observed in conventional polling methods.

Theme	Cluster Numbers	Examples
Political and Economic Relations	0, 2	Discussions on China's economic influence and US-China trade relations. Trump accused of lying about trade talks with China.
Human Rights and Political Issues	4, 9, 8	Criticisms of China's actions in Hong Kong, Taiwan, and its totalitarian governance. Allegations of hacking targeting Uyghur Muslims.
Cultural and Social Commentary	1, 3	Comments on sports events in China, such as UFC. References to cultural exchanges and film festivals involving China.
Miscellaneous	4, 5	Casual mentions of Chinese food. References to characters from Chinese-inspired media.

Table 5: Themes and Clusters in Tweets Regarding China Before COVID-19

Before the COVID-19 pandemic, tweets about China primarily focused on political and economic relations, particularly with the United States. Discussions included the US-China trade war, tariffs, and broader economic implications. Criticisms of both Chinese and US policies were prevalent, analyzing potential outcomes of trade negotiations and their impact on global markets. Human rights issues and government control were also significant themes, with tweets highlighting China's actions in Hong Kong, authoritarian governance, and human rights abuses against Uyghur Muslims. Additionally, there was considerable discourse on cultural engagement, including sports events, film festivals, and references to Chinese-inspired media. Taiwan's political landscape was another prominent topic, intersecting with broader international relations themes.

After the COVID-19 pandemic began, the focus of tweets shifted dramatically to the immediate and severe impacts of the health crisis. A new thematic cluster emerged, concentrating on the immediate health crisis response, reporting new COVID-19 cases, deaths,

Theme	Cluster Numbers	Examples
Political and Economic Relations	1, 6	Criticisms of Chinese influence on global businesses. Discussions on economic policies and sanctions.
Human Rights and Political Issues	0, 4, 6	Criticisms of Chinese government's human rights abuses, especially against Uyghurs. Discussions on religious oppression and government policies.
COVID-19 Impact	2, 3	Discussions on COVID-19's origin and its global implications. References to travel restrictions and health impacts.
Cultural and Social Commentary	7	Criticisms of Chinese government control over media. Conspiracy theories about Chinese influence in other countries.
Miscellaneous	5	Comments on religious oppression. References to conspiracy theories related to Chinese government policies.

Table 6: Themes and Clusters in Tweets Regarding China After COVID-19

and the pandemic's impact on cultural and economic events. Discussions on political and economic relations intensified, scrutinizing China's handling of the pandemic, its influence on global businesses, and implications for international security. Human rights issues remained critical, with increased attention to specific incidents of violence and oppression, particularly against minority groups. Cultural and social commentary persisted but became more intertwined with political and human rights discussions, reflecting the broader impact of China's actions on global culture and society.

The topic modeling results from before and after November 2019 reveal both consistency and differences in the themes discussed on social media. Common themes such as Human Rights and Government Control (Clusters 1, 6, 0) and International Relations (Cluster 4) remained prevalent both before and after the COVID-19 outbreak. This consistency underscores a persistent global concern regarding China's governance style and its implications

Theme	Before COVID-19	After COVID-19
Political and Economic Relations	Discussions on US-China trade, tariffs, and political figures.	Focus on sanctions, economic policies, and global business influence.
Human Rights and Political Issues	Criticism of China's governance, especially in Hong Kong.	Increased focus on human rights abuses, especially against Uyghurs.
COVID-19 Impact	N/A	Discussions on the pandemic's origin, travel restrictions, and health impacts.
Cultural and Social Commentary	References to cultural events, sports, and Chinese-inspired media.	Criticisms of Chinese government control over media and cultural practices.
Miscellaneous	Casual mentions of Chinese food, hacking, and iconic characters.	Conspiracy theories and comments on religious oppression.

Table 7: Comparison of Themes in Tweets Regarding China Before and After COVID-19

for freedom. However, the analysis also noted shifts in topics: discussions on Cultural and Pop Culture Engagement, and Taiwan's Political Landscape (Cluster 5) were prominent before the outbreak but receded afterward. This transition from cultural influence and engagement to a focus on crisis management and health reflects a natural shift in global priorities in response to the pandemic. Such a shift could amplify negative sentiment toward China, as the discourse moved away from potentially positive topics. This change in thematic focus likely contributed to the immediate negative reactions towards China captured by social media data, highlighting how social media's rapid response to current events can influence public sentiment more swiftly than traditional polling methods. The topic modeling analysis highlighted a significant change with the emergence of the Immediate Health Crisis Response (Cluster 7), a topic cluster that developed specifically in response to the outbreak. This cluster concentrated on reporting new COVID-19 cases, deaths, and the pandemic's impact on major cultural and economic events, like the release of the movie "Mulan." This change underscores the ability of social media data to capture and reflect public sentiment regarding immediate social events promptly, as also seen in studies on the immediacy and reach of social media platforms (Jungherr 2015).

6.2.2 Russia

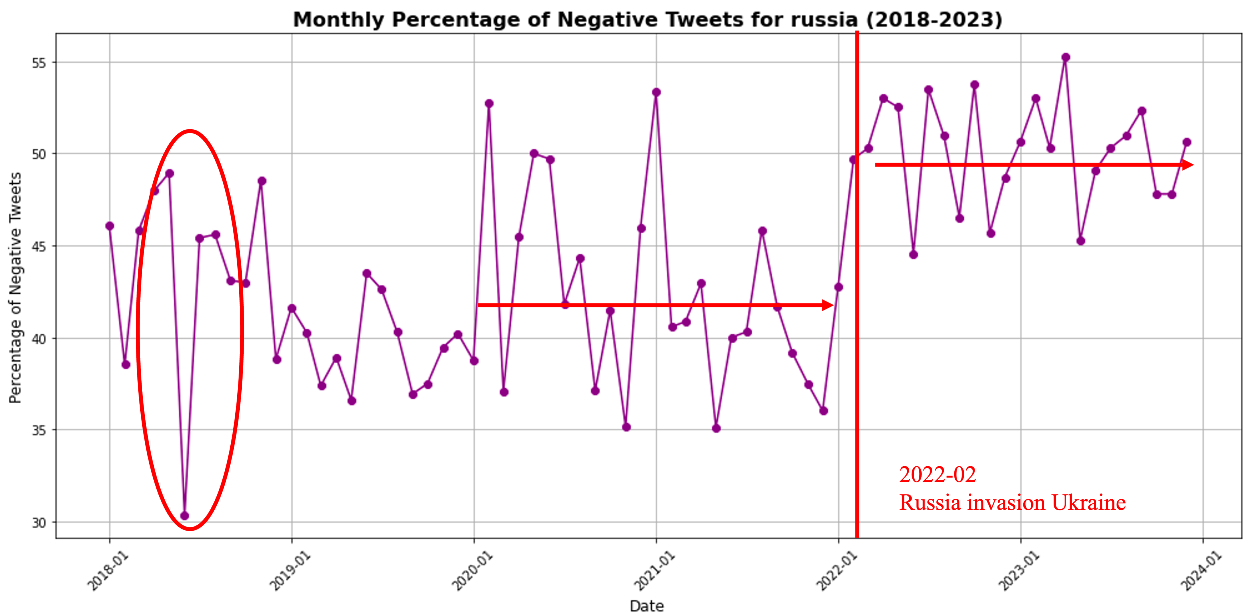

Figure 6: Sentiment Analysis for Russia

The monthly sentiment analysis results for Russia from social media also display notable differences compared to the trends predicted by Gallup data, including more monthly fluctuations and a later increase in negative sentiment. While Gallup data suggested an increase in negative sentiment towards Russia beginning in 2019, social media data did not show this trend until 2020. Although the general trend observed through the social media-based approach aligns with the Gallup polling method over the long term, this mismatch underscores the need for further exploration. Conducting Topic Modeling analysis may help identify potential reasons for these differences. Additionally, as highlighted in the sentiment movement figure, there was an immediate increase in the percentage of negative tweets regarding Russia following the invasion of Ukraine in February 2022. This rapid shift was not reflected in the Gallup data, mirroring a similar discrepancy observed with China's COVID-19 outbreak, where social media captured immediate public reactions that Gallup data did not detect. This further illustrates the responsiveness of social media analysis in capturing real-time changes in public sentiment, which traditional polling methods may miss due to their timing and methodology.

In this specific case, while discussions about the Russia-Ukraine issue had been circulating long before any direct conflict, actual military actions were not initiated until February 2022. This timing coincides with when Gallup data collection also occurred, suggesting that not all participants might have been fully aware of these developments at the time of polling. Consequently, Gallup data may not have captured the immediate spike in negative public opinion toward Russia that coincided with the commencement of military actions. In contrast, social media, known for its capability to facilitate immediate discussions and report the latest news, was able to reflect this surge in negativity more promptly. This responsiveness highlights the advantage of social media data in capturing real-time shifts in public sentiment, particularly in response to rapid developments, a capability that traditional polling methods might lack due to their inherent time lag. Furthermore, this dynamic also supports the rise in the percentage of negative tweets beginning in December 2019, as the Ukraine issue has been a topic of discussion since that year, demonstrating how social media can serve as an early indicator of escalating sentiments.

According to the topic modeling results, before the invasion, the discourse surrounding Russia was varied, blending skepticism towards Russian policies with awareness of brew-

Theme	Cluster Numbers	Examples
Political Relations	5, 2, 4, 6	Discussions on Trump-Russia collusion, election interference, and Russian influence on US politics. Criticisms of Obama's and Trump's policies towards Russia.
Sports and Culture	2, 3	Comments on the World Cup and other sports events in Russia. Travel experiences and cultural exchanges.
Russian Politics and Human Rights	6, 0, 1	Criticisms of Russian government corruption and its actions in Syria. Allegations of Russia's interference in global politics and human rights abuses.
Miscellaneous	1, 7	References to Edward Snowden's criticisms of the Russian government. Discussions on various international investments and business dealings involving Russia.

Table 8: Themes and Clusters in Tweets Regarding Russia Before the Invasion of Ukraine

ing geopolitical tensions, notably regarding Ukraine. However, these discussions frequently included elements of humor and cultural celebration, such as New Year greetings and historical reflections, which moderated the overall negative tone. The discourse was characterized by a mix of internal censorship and propaganda topics alongside cautious mentions of aggression towards Ukraine, resulting in a balanced public dialogue that maintained a mix of criticism and cultural content.

In stark contrast, after the invasion began, the discourse shifted markedly towards the immediate and severe consequences of Russia's actions and topics including humanitarian, legal, and geopolitical repercussions of Russia's actions in Ukraine. Both pre-and post-invasion phases recognized the underlying geopolitical tensions between Russia and Ukraine, though the actual invasion dramatically escalated the context from potential to realized aggression. The tone of conversations became significantly negative, dominated by urgency and the seriousness of the issues at hand. The focus centered on the resilience of

Theme	Cluster Numbers	Examples
Political Relations	1, 8, 2, 5, 0	Discussions on the geopolitical threat posed by Russia and its economic activities. Criticisms of Trump's connections to Russia and the implications for US security.
Russian Actions in Ukraine	2, 7, 6	Criticisms of Russian actions in Ukraine and Crimea. Discussions on human rights abuses and political oppression by Russia.
Sports and Culture	1, 4, 9	Comments on sports events and cultural interactions involving Russia. Discussions on Russia's influence in various global contexts.
Miscellaneous	3, 5, 7	Criticisms of corruption and deception in politics related to Russia. Various international and domestic political issues involving Russia.

Table 9: Themes and Clusters in Tweets Regarding Russia After the Invasion of Ukraine

Ukrainian citizens, the international condemnation of Russia, and emphatic calls for justice against perceived war crimes and genocidal actions. This period saw a definitive shift from speculative and anticipatory discussions to real-time responses and demands for substantial international action against Russia.

This result further justifies the increase in the percentage of negative posts starting from 2019, as discussions around the Russia-Ukraine issue were already escalating public sentiment. With this in mind, the results also shed light on the reasons behind the relatively stable public opinion captured by Gallup data before and after the onset of direct military actions in Russia. Specifically, it is possible that Gallup observed a stable movement of public opinion towards Russia because the prevailing perceptions regarding the Russia-Ukraine issue were already well-established before the Gallup polling was conducted. This suggests that the participants may have already formed their opinions on the matter, which did not significantly change in the immediate aftermath of the conflict's escalation, reflecting

Theme	Before Invasion	After Invasion
US-Russia Relations	Discussions on Trump-Russia collusion, election interference, and Russian influence on US politics. Criticisms of Obama's and Trump's policies towards Russia.	Discussions on the geopolitical threat posed by Russia and its economic activities. Criticisms of Trump's connections to Russia and the implications for US security.
Russian Actions in Ukraine	N/A	Criticisms of Russian actions in Ukraine and Crimea.
Russian Politics and Human Rights	Criticisms of Russian government corruption and its actions in Syria. Allegations of Russia's interference in global politics and human rights abuses	Discussions on human rights abuses and political oppression by Russia.
Sports and Culture	Comments on the World Cup and other sports events in Russia. Travel experiences and cultural exchanges.	Comments on sports events and cultural interactions involving Russia. Discussions on Russia's influence in various global contexts.
Miscellaneous	References to Edward Snowden's criticisms of the Russian government. Discussions on various international investments and business dealings involving Russia.	Criticisms of corruption and deception in politics related to Russia. Various international and domestic political issues involving Russia.

Table 10: Comparison of Themes in Tweets Regarding Russia Before and After the Invasion of Ukraine

a pre-existing consensus in public sentiment as captured by traditional polling methods.

6.2.3 North Korean

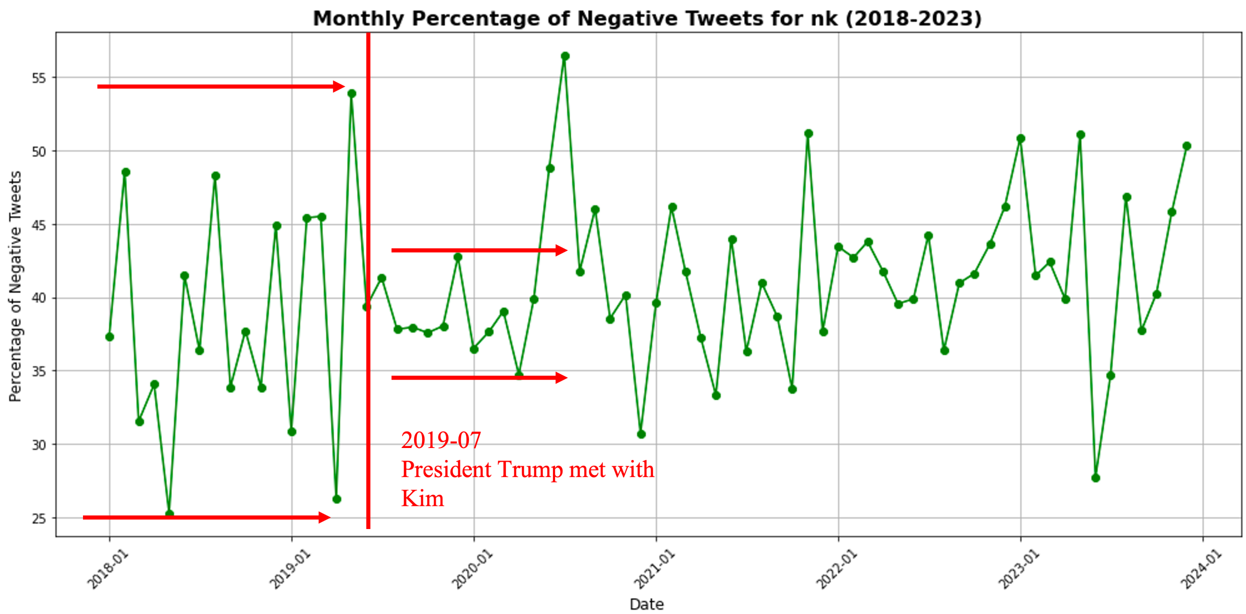

Figure 7: Sentiment Analysis for North Korean

The figure depicts social media public opinion analysis results for North Korea and highlights significant monthly fluctuations from 2018 to 2023, which contrasts with the Gallup polling method that focuses solely on February each year. This discrepancy suggests that over time, U.S. citizens' opinions on North Korea have varied, with an average negative tweet percentage of 40%. Notably, between mid-2019 and early 2020, the graph shows a relatively stable trend compared to the rest of the period, which is characterized by high volatility. To investigate the reasons behind this stability, I employed topic modeling analysis on the data from this stable period and compared it to the data from the preceding period. This approach aims to uncover any shifts in the themes or topics discussed that may have influenced the stabilization of public sentiment towards North Korea during this time. Understanding these dynamics can provide deeper insights into the factors that drive changes in public opinion as reflected in social media content.

Theme	Cluster Numbers	Examples
Political Relations	5, 2, 3, 1	Kim-Putin summit and North Korea's pivot towards Russia. Russia's role in North Korea's nuclear negotiations.
Human Rights Issues	9, 0	Executions of North Korean officials. Defectors' experiences and regime oppression.
Nuclear Concerns	8, 3, 1	North Korea's nuclear developments. Satellite imagery tracking nuclear activities.
Miscellaneous	4, 6, 7	North Korea's cyber capabilities. Cultural aspects and defectors' stories.

Table 11: Themes and Clusters in Tweets Regarding North Korea Before Trump's Meeting with Kim Jong-un

According to the topic modeling results for tweets before Trump's meeting with Kim Jong-un, tweets about North Korea were focused on its diplomatic interactions, particularly with Russia. The discussions highlighted the Kim-Putin summit and North Korea's efforts to strengthen ties with Russia amidst ongoing denuclearization negotiations. Human rights abuses within North Korea were a significant topic, with tweets mentioning the execution of officials and stories from defectors detailing the regime's brutality. Concerns about North Korea's nuclear capabilities were also prominent, with discussions on nuclear developments and the use of satellite imagery to track progress. Other topics included North Korea's cyber capabilities, cultural aspects, and the impact of US policies.

After the meeting, the focus of tweets shifted to the direct outcomes and political dynamics resulting from the summit. Discussions centered on Trump's interactions with Kim Jong-un, including controversial statements and decisions, highlighting North Korea's continued missile tests and the strained negotiations between the two countries. Human rights issues remained critical, with increased emphasis on specific incidents of persecution and

Theme	Cluster Numbers	Examples
Political Relations	5, 9, 3	Trump's comments on North Korea. North Korea's missile tests and strained negotiations.
Human Rights Issues	5, 1, 9, 4	Persecution of North Korean citizens. Oppressive actions and anti-Semitic behavior.
Nuclear Concerns	6, 9, 2	Continued nuclear tests and missile launches. Implications for regional and global security.
Miscellaneous	4, 7, 8	Cultural commentary and media depictions. Cyber activities and international policy impacts.

Table 12: Themes and Clusters in Tweets Regarding North Korea After Trump's Meeting with Kim Jong-un

oppression by the regime. Concerns about North Korea's nuclear activities persisted, with renewed urgency in analyzing the implications for regional and global security. Other tweets included cultural commentary, media depictions of North Korea, and the impact of international policies on the country's behavior.

Theme	Before Meeting	After Meeting
Political Relations	Kim-Putin summit and North Korea's pivot towards Russia. Russia's role in North Korea's nuclear negotiations.	Trump's comments on North Korea. North Korea's missile tests and strained negotiations.
Human Rights Issues	Executions of North Korean officials. Defectors' experiences and regime oppression.	Persecution of North Korean citizens. Oppressive actions and anti-Semitic behavior.
Nuclear Concerns	North Korea's nuclear developments. Satellite imagery tracking nuclear activities.	Continued nuclear tests and missile launches. Implications for regional and global security.
Miscellaneous	North Korea's cyber capabilities. Cultural aspects and defectors' stories.	Cultural commentary and media depictions. Cyber activities and international policy impacts.

Table 13: Comparison of Themes in Tweets Regarding North Korea Before and After Trump's Meeting with Kim Jong-un

Throughout both periods, there is a consistent focus on North Korea's geopolitical strategies, including its interactions with major global powers and nuclear ambitions, reflecting ongoing international concerns about the country's impact on regional and global stability. Discussions on human rights abuses within North Korea, such as persecution, surveillance, and harsh punishments, also persist, emphasizing the global attention to humanitarian issues within the country. Additionally, the leadership of Kim Jong Un and the regime's use of propaganda to influence domestic and international perceptions remain common topics. However, there are notable differences between the periods, particularly in the intensity and detail of the discussions. During periods of high fluctuation, there is an increased focus on specific diplomatic events, such as summits and high-level meetings, suggesting that active diplomacy periods lead to more concentrated discussions on potential diplomatic outcomes. This period also features more detailed discussions on military strategies and security concerns, likely driven by specific events or announcements regarding North Korea's military capabilities. Furthermore, discussions about economic sanctions and North Korea's responses are more intense during the fluctuating period, highlighting the immediate effects of international economic pressures on the regime, which also supported by Tufekci's research on social media responsiveness (Tufekci 2014). These insights suggest that social media discussions adapt to reflect the evolving geopolitical landscape and specific events, providing a dynamic view of public opinion and discourse regarding North Korea.

Given the discrepancies and similarities observed during the topic modeling, the stability observed might be able to be attributed to several factors. Firstly, the lack of provocative events from North Korea, such as missile tests or military maneuvers, likely contributes to a stable narrative. During these quieter times, the international conversation may continue to address ongoing issues such as human rights abuses or economic sanctions, but without the heightened urgency that new provocative actions would provoke. Secondly, stability in discourse might also reflect periods where international policy approaches towards North Korea remain consistent. Without significant shifts in policy from major stakeholders like the United States, South Korea, or China, there tends to be less fluctuation in the discussions. Additionally, the focus of global media on other pressing international issues can lead to less dramatic coverage of North Korea, contributing to stability in discourse unless significant events occur to shift the media's attention back to the region. These factors combined suggest that the ebb and flow of media attention and international policy significantly influence the stability and intensity of discourse surrounding North Korea.

6.2.4 Iran

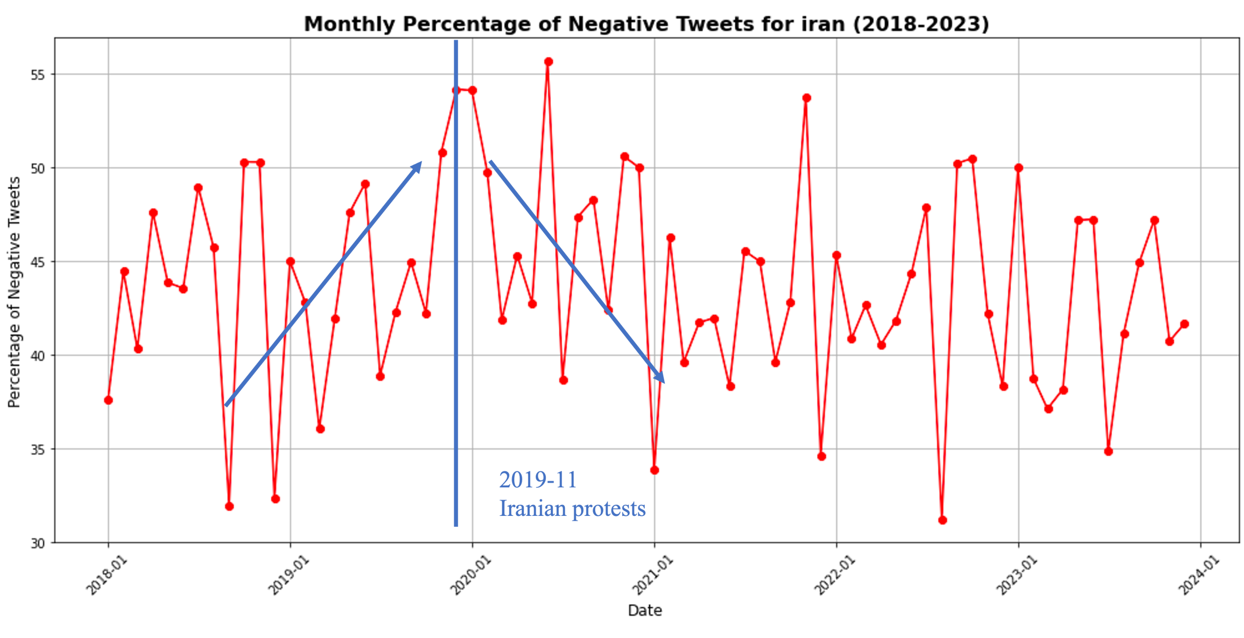

Figure 8: Sentiment Analysis for Iran

Overall, the analysis of the monthly percentage of negative tweets for Iran indicates a fluctuating sentiment pattern, with an initial increase in negativity until early 2020 followed by a subsequent decrease. This trend in social media sentiment aligns with the predictions made by Gallup data, suggesting a consistent perception across different platforms. Similarly, the alignment between social media sentiment trends and Gallup data further supports the viability of using social media platforms as a supplementary tool for public opinion analysis. This correlation underscores the accuracy of social media in reflecting public opinion movements, demonstrating its effectiveness in capturing real-time changes and nuances in sentiment. Given the Iranian protests in November 2019, I expected to see an increase in negativity towards Iran after this event. However, both Gallup and Twitter data indicate a decrease in negativity following the protests. To understand this unexpected trend, I examined the sentiment data for the five months before and after November 2019. This deeper analysis aims to identify specific themes and shifts in public sentiment that may have influenced or resulted from the protests, providing a more nuanced understanding of how social events impact public opinion as reflected through social media.

Theme	**Cluster Numbers**	**Examples**
Political Relations	0, 5, 7	US-Iran tensions, covert cooperation with Russia. Criticisms of Trump's tweets on Iran.
Human Rights Issues	0, 5, 3	Calls for the release of Nazanin Zaghari-Ratcliffe. Impact of conflicts involving Iran.
Nuclear Concerns	5, 2	Rouhani's warnings on nuclear steps. Criticisms of Iran's nuclear ambitions and related behaviors.
Miscellaneous	3, 4, 1, 6	Trump's disclosure of satellite imagery. Ahmadinejad's tweets. Historical findings related to Persia.

Table 14: Themes and Clusters in Tweets Regarding Iran Before the Protests

Before the protests, the discourse on Iran predominantly focused on political relations with the US, human rights issues, and nuclear concerns. Tweets discussed US-Iran tensions, covert cooperation with Russia, and frequent criticisms of President Trump's policies and statements regarding Iran. There was notable advocacy for the release of individuals like Nazanin Zaghari-Ratcliffe and concerns about the impact of conflicts involving Iran. Additionally, Iran's nuclear ambitions were a significant topic, with discussions on Rouhani's warnings and international criticisms of Iran's nuclear activities. Miscellaneous topics included Trump's disclosure of satellite imagery, Ahmadinejad's social media presence, and historical findings related to Persia.

Theme	Cluster Numbers	Examples
Political Relations	8, 1, 6	US airstrikes and Trump's stance on Iran. Iran's nuclear ambitions and consequences.
Human Rights Issues	1, 5, 9, 4	Assaults on civilians by Iranian authorities. Anti-Semitic actions and oppression in Iran.
Nuclear Concerns	4, 0, 6	Iran's nuclear deal at risk. Discussions on Iran's nuclear activities and their implications.
Miscellaneous	7, 3, 2	Cultural aspects and social commentary on Iran. Iran's impact on regional and global politics.

Table 15: Themes and Clusters in Tweets Regarding Iran After the Protests

After the protests, the narrative shifted to more immediate and intense political events, such as US airstrikes and the Trump administration's aggressive stance towards Iran. The discourse on Iran's nuclear ambitions became more urgent, with heightened focus on the potential consequences and international responses. Human rights issues gained significant attention, highlighting specific incidents of violence and oppression by Iranian authorities, including assaults on civilians and anti-Semitic actions. Cultural and social commentary about Iran became more intertwined with political and human rights discussions, reflecting on Iran's broader impact on regional and global politics.

Theme	Before Protests	After Protests
Political Relations	US-Iran tensions, covert cooperation with Russia. Criticisms of Trump's tweets on Iran.	US airstrikes and Trump's stance on Iran. Iran's nuclear ambitions and consequences.
Human Rights Issues	Calls for the release of Nazanin Zaghari-Ratcliffe. Impact of conflicts involving Iran.	Assaults on civilians by Iranian authorities. Anti-Semitic actions and oppression in Iran.
Nuclear Concerns	Rouhani's warnings on nuclear steps. Criticisms of Iran's nuclear ambitions and related behaviors.	Iran's nuclear deal at risk. Discussions on Iran's nuclear activities and their implications.
Miscellaneous	Trump's disclosure of satellite imagery. Ahmadinejad's tweets. Historical findings related to Persia.	Cultural aspects and social commentary on Iran. Iran's impact on regional and global politics.

Table 16: Comparison of Themes in Tweets Regarding Iran Before and After the Protests

Given the topic modeling results, common themes such as geopolitical and military concerns and human rights issues persist across both periods. However, specific discussions vary significantly. The discourse before the protests was broader and more generalized, covering a range of geopolitical, nuclear, and human rights concerns. After the protests, the discourse shifted notably towards more immediate issues related to the protests themselves. The humanitarian crisis, marked by the government's violent suppression of demonstrators and the resulting casualties, became a focal point. Social media platforms rapidly filled with firsthand accounts of the crackdown, images of the protests, and international reactions condemning the actions of the Iranian government. For instance, tweets and posts often included calls for international intervention or support for the protesters, reflecting a surge in global solidarity and advocacy for human rights in Iran. This shift is also evident in the increased attention from international figures and organizations post-protests, which could be seen in public statements from global leaders or resolutions in international bodies like the United Nations, calling for investigations and actions against human rights violations in Iran.

7 Discussion

7.1 Predict Public Opinion in General Pattern as a supplementary tool

In this research, I utilize Twitter data from February of each year to analyze the percentage of negative tweets regarding specific countries, comparing these results with Gallup polling outcomes. The analysis reveals a high degree of similarity between the two data sources in tracking public opinion trends across the four examined countries, demonstrating the effectiveness of social media in supplementing traditional polling methods for gauging public sentiment. Importantly, the findings highlight Twitter's capacity to capture rapid shifts in public sentiment, particularly in response to significant geopolitical events. For example, Twitter data showed a sharp increase in negative sentiment towards China immediately following the COVID-19 outbreak in November 2019—a trend that was not reflected in the Gallup data collected in February 2020, which indicated more stable sentiment levels. Similarly, the invasion of Ukraine by Russia in February 2022 resulted in an immediate spike in negative tweets about Russia, a significant change that was again not captured by Gallup polling.

These instances underscore social media's ability to provide real-time insights into public opinion (Skoric et al. 2015), capturing immediate reactions to global events much faster than traditional polling methods. The discrepancies noted, especially in the speed with which social media responds to unfolding events compared to the slower, more methodical approach of Gallup, suggest that integrating social media insights could significantly enhance the comprehensiveness and timeliness of public opinion assessments. This ability to quickly reflect public sentiment makes social media a valuable tool for understanding and predicting public opinion dynamics, particularly in a rapidly changing global landscape.

7.2 Social Media Lagging

During the analysis of public opinion trends in Russia and Iran, a time lag was observed when using social media to predict public sentiment, suggesting that assessments based on social media tend to persist longer than those derived from Gallup data. This is evident in scenarios reacting to major social events or natural movements within societal discourse. For instance, in the case of Iran, social media data indicated a slower decline from the peak of negative sentiment following the Iranian protests compared to Gallup data. Similarly, such a slower decline could also be seen for North Korean data after 2018. This phenomenon can be attributed to social media's inherent capabilities to archive historical data and sustain prolonged discussions.

Social media platforms naturally extend the lifecycle of public engagement with specific topics due to their format and operational mechanisms, enabling discussions to continue well beyond the immediate aftermath of an event. People on these platforms may continue to discuss an event months after its occurrence, meaning that social media-based public opinion is more likely to be influenced by these extended discussions. Consequently, social media sentiment may exhibit a longer recovery time from the impact of social events. In contrast, Gallup polling, which typically involves targeting participants for in-person surveys, may reflect a more immediate but less enduring impact of events on public sentiment. This difference is partly due to the limitations of human memory, which may not retain the influence of past events as strongly or as long as the digital records of social media do. Therefore, while social media provides a broader window into historical public sentiment, traditional polling methods like Gallup offer a snapshot that may underrepresent the lingering effects of past events on current public opinion.

7.3 Immediacy of Social Media

The immediacy of social media in reflecting major social events was prominently identified in this study. According to the analysis of data from China and Russia, in comparison with Gallup data, the sentiment index on social media responded promptly and immediately following the COVID-19 outbreak and the invasion of Ukraine. Moreover, the results of topic modeling showed that discussions on social media intensified after these events, further supporting the credibility of social media's ability to quickly reflect public opinion, a characteristic supported by research on social media's real-time responsiveness (Tufekci 2014). In comparison with the lag observed in social media's recovery from social events, it is actually more sensitive to social events and political policies. This sensitivity highlights social media's role as a real-time indicator of public sentiment, offering a more immediate gauge than traditional polling methods such as Gallup, which tend to have a delay in reflecting shifts in public opinion. This characteristic underscores social media's role as a real-time indicator, offering a more immediate gauge than traditional polling methods (Kursuncu et al. 2019).

7.4 Susceptible to Social Event

In the context of my research, the analysis of public opinions on social media reveals a landscape that is inherently more reactive and sensitive to political and social events, highlighting the immediacy of social media and a slower rate of recovery. This sensitivity is exemplified by the volatility of sentiment scores in response to such events, which can lead to pronounced swings in the perceived public mood. Social media platforms, by their very design, facilitate the rapid dissemination and discussion of information, allowing users to instantly express their views on current affairs. This immediacy means that during significant political developments or social upheavals, these platforms can quickly become hotbeds of intensity. For example, amidst the tumult of Iran's protests concerning the tragic demises and incarcerations of students, social media platforms were adept at capturing the ebb and flow of public sentiment toward the government and the country. This finding is supported by existing literature that highlights the reactive nature of social media, where major events can dominate and shape public opinion more intensely than traditional methods (Howard et al. 2021).

While social media data excel in depicting the fluid nature of public opinion, their sensitivity, and the resulting immediacy also introduce a lag in recovering from the immediate impacts of social events, which can compromise their accuracy and stability when assessing the general public's sentiment under conventional definitions. This lagging quality means that while social media is effective in capturing rapid shifts in sentiment, it may take longer for these platforms to stabilize and reflect a more balanced view.

Another possible reason for the heightened sensitivity of social media towards major events is the natural decline in discussions on less critical topics when significant social or political events occur. This phenomenon was evident in the analysis of China's social media activity, where discussions on cultural events and related news decreased significantly following the COVID-19 outbreak. As a result, the reduction in positive or neutral tweets and discussions amplified the negative influence of major events on how people perceive

China. This shift in focus can lead to an exaggerated representation of sentiment related to the event, as the usual balance of discourse is disrupted, and more attention is concentrated on the pressing issue. Such dynamics underscore the reactive nature of social media, where the immediate impact of significant events can overshadow ongoing conversations, thereby shaping the public opinion landscape in a more pronounced manner.

7.5 Other Limitations

The study's limitations encompass key aspects. Firstly, the utilization of a limited number of tweets, amounting to a mere 160 per month, raises concerns regarding the representativeness of the findings in capturing the overall sentiment of the population. This limitation stems from various factors, including computational constraints, the selection of keywords, and Twitter's restrictions on data scraping. Consequently, the study's results may be influenced, potentially underestimating the ability of social media to reflect public opinion.

Secondly, the exclusive focus on Twitter and Gallup as the primary subjects of investigation restricts the generalizability of the findings to other social media platforms. Consequently, the applicability of the study's conclusions to different online platforms may be limited. Thirdly, the study's narrow examination of a singular public opinion topic, namely the public opinion of US citizens towards other countries, constrains the extent to which the findings can be applied to other subjects. Thus, the study's outcomes may not provide a comprehensive understanding of public opinion. Furthermore, the study's methodology lacks sophisticated approaches to establishing the relationship between public sentiment scores and actual behavioral patterns. Lastly, the choice of keywords employed in the study can influence the resulting findings, and it is plausible that the selected keywords fail to capture the complete range of public opinion on the topic under investigation.

These limitations underscore the need for a cautious interpretation of the study's intriguing findings, and they underscore the necessity for additional research to comprehensively elucidate the distinctions between social media-based public opinion and traditional public opinion surveys.

8 Conclusion

In conclusion, the findings from this research suggest that social media can be a valuable supplementary tool in public opinion analysis, demonstrating its effectiveness and qualities in several key areas:

- **General Trend Prediction:** Twitter and Gallup data have shown a similarity in tracking public opinion trends across various countries. This suggests that social media can effectively mirror traditional polling methods in predicting general trends.
- **Time Lagging and Recovery from Social Events:** Social media exhibits a distinctive characteristic in its response to social events—it tends to sustain engagement longer than traditional polls. This extended discussion period might result in a time lag in recovering from the immediate impacts of significant events.
- **Immediacy of Reflecting Social Events:** Social media's strength lies in its immediacy, capable of reflecting rapid shifts in sentiment faster than traditional polling methods. This immediacy is particularly evident during major geopolitical or social crises.

- **Increased Susceptibility to Social Events:** The structure and nature of social media also mean that when significant events happen, there is a natural suppression of less critical discussions. This suppression shifts the focus towards those significant events, concentrating public discourse on the issue at hand. This overconcentration can amplify the perceived impact of the event on public sentiment, making social media a sensitive barometer of public mood in response to current events.

Overall, social media platforms provide valuable insights into public sentiment, making them an effective supplementary tool for public opinion analysis. By combining the real-time, dynamic data from social media with the methodological rigor of traditional polls, researchers and policymakers can achieve a more nuanced and timely understanding of public opinion.

Data and Code Availability Statement

The code and data associated with this project are available on GitHub at https://github.com/ChrisZhang6888/public_opinion_thesis.git. The repository is organized into directories based on different components or stages of the project (Zhang, n.d.).

The code for this project can be found in the GitHub repository mentioned above. It is structured into Jupyternotebook files, each containing the necessary code for cleaning, visualization, and analyzing sections. Please refer to the README file in each directory for instructions on how to run the code and any additional dependencies required.

The dataset used in this project is stored in the GitHub repository along with the code. I segregated them into two parts including Gallup data and Twitter data. Please navigate to the repository mentioned above to access the dataset.

References

Anstead, Nick and Ben O'Loughlin (Mar. 2015). "Social Media Analysis and Public Opinion: The 2010 UK General Election". en. In: *Journal of Computer-Mediated Communication* 20.2, pp. 204–220. ISSN: 10836101. DOI: 10.1111/jcc4.12102. URL: https://academic.oup.com/jcmc/article/20/2/204-220/4067564 (visited on 04/17/2024).

Barberá, Pablo et al. (Oct. 2015). "Tweeting From Left to Right: Is Online Political Communication More Than an Echo Chamber?" en. In: *Psychological Science* 26.10. Publisher: SAGE Publications Inc, pp. 1531–1542. ISSN: 0956-7976. DOI: 10.1177/0956797615594620. URL: https://doi.org/10.1177/0956797615594620 (visited on 04/17/2024).

Bollen, Johan, Huina Mao, and Alberto Pepe (2011). "Modeling Public Mood and Emotion: Twitter Sentiment and Socio-Economic Phenomena". en. In: *Proceedings of the International AAAI Conference on Web and Social Media* 5.1. Number: 1, pp. 450–453. ISSN: 2334-0770. DOI: 10.1609/icwsm.v5i1.14171. URL: https://ojs.aaai.org/index.php/ICWSM/article/view/14171 (visited on 04/17/2024).

David, Caleb (July 2023). *Twitter Scraper · Apify*. en. URL: https://apify.com/microworlds/twitter-scraper (visited on 04/05/2024).

Devlin, Jacob et al. (May 2019). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. arXiv:1810.04805 [cs]. DOI: 10.48550/arXiv.1810.04805. URL: http://arxiv.org/abs/1810.04805 (visited on 05/17/2024).

Dodds, Peter Sheridan et al. (Dec. 2011). "Temporal Patterns of Happiness and Information in a Global Social Network: Hedonometrics and Twitter". en. In: *PLOS ONE* 6.12. Publisher: Public Library of Science, e26752. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0026752. URL: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0026752 (visited on 05/20/2024).

Edwards-Levy Ariel (2021). *Here's what pollsters think happened with 2020 election surveys — CNN Politics*. URL: https://www.cnn.com/2021/05/13/politics/2020-polling-error-research/index.html?utm_term=link&hx0026;utm_source=twCNN&hx0026;utm_medium=social&hx0026;utm_content=2021-05-14T12%3A52%3A28 (visited on 04/17/2024).

Gallup, Inc (Mar. 2023). *Americans Continue to View China as the U.S.'s Greatest Enemy*. en. Section: Politics. URL: https://news.gallup.com/poll/471494/americans-continue-view-china-greatest-enemy.aspx (visited on 11/09/2023).

Gao, Yuqi, Hang Hua, and Jiebo Luo (2021). "Analyzing public opinion on COVID-19 through different perspectives and stages". en. In: *APSIPA Transactions on Signal and Information Processing* 10.1. ISSN: 2048-7703, 2048-7703. DOI: 10.1017/ATSIP.2021.

5. URL: http://www.nowpublishers.com/article/Details/SIP-172 (visited on 03/29/2023).

GroNLP/hateBERT · Hugging Face (2024). URL: https://huggingface.co/GroNLP/hateBERT (visited on 05/12/2024).

Historical Development of Public Opinion (2024). en. DOI: 10.1086/220561. URL: https://www.journals.uchicago.edu/doi/epdf/10.1086/220561 (visited on 04/17/2024).

Howard, Joshua et al. (Feb. 2021). "Student Motivation and Associated Outcomes: A Meta-Analysis From Self-Determination Theory". In: *Perspectives on Psychological Science*. DOI: 10.1177/1745691620966789.

Hutto, C. J. (Apr. 2024). *cjhutto/vaderSentiment*. original-date: 2014-11-17T16:31:45Z. URL: https://github.com/cjhutto/vaderSentiment (visited on 04/27/2024).

Jungherr, Andreas (2015). "Twitter in the Analysis of Social Phenomena: An Interpretative Framework". en. In: *Analyzing Political Communication with Digital Trace Data: The Role of Twitter Messages in Social Science Research*. Ed. by Andreas Jungherr. Cham: Springer International Publishing, pp. 25–68. ISBN: 978-3-319-20319-5. DOI: 10.1007/978-3-319-20319-5_3. URL: https://doi.org/10.1007/978-3-319-20319-5_3 (visited on 05/17/2024).

Klašnja, Marko et al. (Sept. 2018). "Measuring Public Opinion with Social Media Data". In: *The Oxford Handbook of Polling and Survey Methods*. Ed. by Lonna Rae Atkeson and R. Michael Alvarez. Oxford University Press, p. 0. ISBN: 978-0-19-021329-9. DOI: 10.1093/oxfordhb/9780190213299.013.3. URL: https://doi.org/10.1093/oxfordhb/9780190213299.013.3 (visited on 11/02/2023).

Klingeren, Marijn van, Damian Trilling, and Judith Möller (July 2021). "Public opinion on Twitter? How vote choice and arguments on Twitter comply with patterns in survey data, evidence from the 2016 Ukraine referendum in the Netherlands". en. In: *Acta Politica* 56.3, pp. 436–455. ISSN: 0001-6810, 1741-1416. DOI: 10.1057/s41269-020-00160-w. URL: https://link.springer.com/10.1057/s41269-020-00160-w (visited on 03/29/2023).

Kursuncu, Ugur et al. (Jan. 2019). "Predictive Analysis on Twitter: Techniques and Applications". In: pp. 67–104. ISBN: 978-3-319-94104-2. DOI: 10.1007/978-3-319-94105-9_4.

Michael, Gabriel and Colin Agur (July 2018). "The Bully Pulpit, Social Media, and Public Opinion: A Big Data Approach". In: *Journal of Information Technology & Politics* 15.3. Publisher: Routledge _eprint: https://doi.org/10.1080/19331681.2018.1485604, pp. 262–277. ISSN: 1933-1681. DOI: 10.1080/19331681.2018.1485604. URL: https://doi.org/10.1080/19331681.2018.1485604 (visited on 04/17/2024).

NLTK :: Natural Language Toolkit (2024). URL: https://www.nltk.org/ (visited on 04/06/2024).

renato (Nov. 2021). *Topic modeling with transformers: farewell LDA*. en. URL: https://renatobudinich.com/topic-modeling-with-transformers/ (visited on 05/17/2024).

Shapiro, Robert Y. (Dec. 2011). "Public Opinion and American Democracy". In: *Public Opinion Quarterly* 75.5, pp. 982–1017. ISSN: 0033-362X. DOI: 10.1093/poq/nfr053. URL: https://doi.org/10.1093/poq/nfr053 (visited on 04/01/2023).

Skoric, Marko et al. (Nov. 2015). "Social media and citizen engagement: A meta-analytic review". In: *New Media & Society* 18. DOI: 10.1177/1461444815616221.

Team, NLTK (2023). *nltk: Natural Language Toolkit*. URL: https://www.nltk.org/ (visited on 05/17/2023).

Tufekci, Zeynep (Mar. 2014). "Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls". In: *Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM 2014* 8. DOI: 10.1609/icwsm.v8i1.14517.

Wu, Yi et al. (Dec. 2011). "An Exploration of Social Media in Public Opinion Convergence: Elaboration Likelihood and Semantic Networks on Political Events". In: *2011 IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing*, pp. 903–910. DOI: 10.1109/DASC.2011.151. URL: https://ieeexplore.ieee.org/document/6118885 (visited on 04/17/2024).

Zhang, Yini, Fan Chen, and Karl Rohe (Jan. 2022). "Social Media Public Opinion as Flocks in a Murmuration: Conceptualizing and Measuring Opinion Expression on Social Media". In: *Journal of Computer-Mediated Communication* 27.1, zmab021. ISSN: 1083-6101. DOI: 10.1093/jcmc/zmab021. URL: https://doi.org/10.1093/jcmc/zmab021 (visited on 04/17/2024).