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Article

Advanced Natural Language Processing Analysis on Cross-Border Media Sentiment from China and South Korea

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Abstract

This research analyzes media sentiment towards China and Korea with in-depth details. The study employs advanced Natural Language Processing (NLP) and sentiment analysis methods to analyze 11,598 documents, including news articles and reports. Through the analyses, the study detects sentiment patterns that reflect the complex geopolitical and economic interactions between the two nations. The study uses transformer-based models for accurate sentiment detection. The findings provide insights into how media narratives may shape and reflect international perceptions. Importantly, the study allows us to compare its outcomes with actual geopolitical events. It also highlights the capability of NLP techniques to understand the nuances of diplomatic relations, confirming the approach's reliability in revealing intricate diplomatic dynamics.

Keywords

China and Korea, International Economics, International Relations, Economic Methodology, Advanced Natural Language Processing (NLP), Sentiment Analysis

Introduction

Nationalism, a powerful and often polarizing force, has shaped the course of history and continues to influence global politics and social dynamics. The emotional and instinctual ties that bind individuals to their nations are not only born out of shared geography or language but also out of a collective sentiment that resonates with the group's history and social experiences.

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As Handman (1921) insightfully observed, these sentiments are central to the development of nationalism, where beliefs and shared memories serve as the bedrock for collective identity.

In the arena of international relations, the interactions between neighboring countries provide a rich tapestry of cooperation and conflict (Schultz, 2015). These relationships are underpinned by a myriad of factors, including but not limited to historical legacies, economic dependencies, cultural affinities, and political alliances. The proximity of these nations often leads to intertwined destinies, where actions taken by one can have immediate and profound effects on the other. This interconnectedness necessitates a delicate balance, as periods of peace and collaboration can swiftly give way to tensions and disputes driven by changes in regional security landscapes, shifts in trade dynamics, or cultural misunderstandings.

Furthermore, the role of the media in shaping perceptions and sentiments across national borders cannot be overstated (Kokeyo, 2023). In an era where information is more accessible than ever, the media possesses an unparalleled ability to influence public opinion and national sentiment (Entman, 2004; Sobkowicz et al., 2012). The narratives propagated through news outlets, social media platforms, and cultural productions play a crucial role in constructing the image of the "other," often serving as a lens through which domestic populations view their neighbors. As noted by Fuentes and Peterson (2021) and further explored by Alawade and Obun-Andy (2024), the media's impact on international relations is profound, with the power to both bridge divides and deepen fissures between nations.

Media outlets often can reflect and amplify national attitudes towards foreign countries, influencing international relations (Berry et al., 2016; Nisbet & Myers, 2011). For instance, how Chinese and Korean media portray each other can affect public sentiment, potentially leading to changes in policy, consumer behavior, and even direct diplomatic relations. The portrayal of critical events, political decisions, and cultural exchanges in the media can either bridge gaps between the two nations or exacerbate misunderstandings and conflicts (e.g., Disputes over kimchi; Gries & Masui, 2022).

Given the media's significant role, it is vital to study cross-border media sentiment to understand how it can reflect and influence the complex dynamics between China and Korea. Such an analysis can offer insights into the undercurrents of bilateral relations, providing a more nuanced understanding of how each country views the other and the implications of these perceptions for regional stability and cooperation.

Even though the nature and importance of relation measurement between two countries is scarce, this area of research deals with a comprehensive understanding of media sentiment at the country level. Media sentiment can significantly fluctuate in response to specific events, such as diplomatic meetings, military conflicts, cultural festivals, or trade agreements. Analyzing these fluctuations provides insights into the responsiveness of media narratives to international developments and their potential to influence public opinion and bilateral relations (e.g., Nagashima, 1970). Fisher et al. (2022) offers a unique perspective on analyzing media sentiment, particularly in the context of foreign policy and diplomatic relations. He collects and analyzes sentiment from hundreds of thousands of articles from state media and foreign affairs ministries of countries like North Korea, China, Russia, and Iran. This analysis provides insights into how governments attempt to influence international perceptions and the impact of media narratives on bilateral relations and public opinion. However, most of research are released in financial aspect (Kearney & Liu, 2014; Kim, 2023; Kim et al., 2023; Soon & Kim, 2023; Tetlock, 2007).

This study analyzes how the media can portray China and Korea, employing English text data and advanced Natural Language Processing (NLP) techniques. It aims to achieve the following four objectives: 1) measure sentiment, 2) identify common themes, 3) understand the relationship between the two countries, and 4) compare how historical events influence media coverage. The concepts-section provides a comprehensive overview of the research methodology and process, and the data section explains the collection of documents methods and general exploration; the measurement section presents the sentiment analysis results and discusses those results. The findings and ways ahead section highlights major contributions of this study and suggests directions for further study. Finally, the study concludes with a summary of its investigations and implications.

Concepts

The overviews and processes of study are divided into three key phases as follows:

1. ***Collections and Initial Analyses of Text Data***: The initial phase involves extensive data collection through scraping news articles, reports, and other media documents related to China and Korea. Following the collection, the study applies NLP techniques to tokenize the titles of these documents and extracts preliminary information. This step sets the foundation for a comprehensive analysis by organizing and preparing the data for deeper examination.
2. ***Sentiment Analysis***: The core of this study lies the sentiment analysis that is conducted by using advanced deep learning models, specifically transformer-based models like FinBERT-FOMC, which have been adapted for economic texts. This phase allows for an automated evaluation of the sentiments expressed in the media concerning the economic and geopolitical dynamics between China and Korea, offering insights into prevailing attitudes and perceptions.
3. ***Verification with Actual Events***: The final phase involves comparing the sentiment analysis results with actual geopolitical and economic events between China and Korea. This comparison aims to validate the reliability of sentiment analysis techniques in accurately reflecting complex international relations and economic sentiments as reported in the media. This step ensures the findings are grounded in reality and enhances the study's credibility by linking the analysis with the real world.

Data

The dataset for this study was obtained through a comprehensive scraping of the ProQuest database, incorporating a broad array of variables such as publication date, title, abstract, document type, publishing company, publisher, and place of publication. And, we focus on a subset of the following variables: 'Publication Date', 'Title', 'Document Type', 'Publisher', and 'Company', to conduct a textual mood analysis across two countries. <Figure 1> illustrates the distribution of document types within the dataset. Most of the data was classified as newspaper articles, followed by wire feeds, magazines, and reports. It is important to note that in this study, the weight attributed to each document type was not considered. This decision was made despite the potential for reports or scholarly journals to exert a relatively higher impact on the market.

<Figure 2> displays the top 20 publishers within the dataset, with 'Asia News Monitor' emerging as the foremost distributor, succeeded by 'The Korea Times' and 'China Daily'. Moreover, <Figure 3> delineates the top 20 organizations or institutions classified as companies in the dataset, with NATO and ASEAN occupying the leading positions.

<Figure 4> illustrates the daily frequency of documents, presenting an overview of the data retrieved from the ProQuest database using the keywords 'China', 'Chinese', 'Korea', and

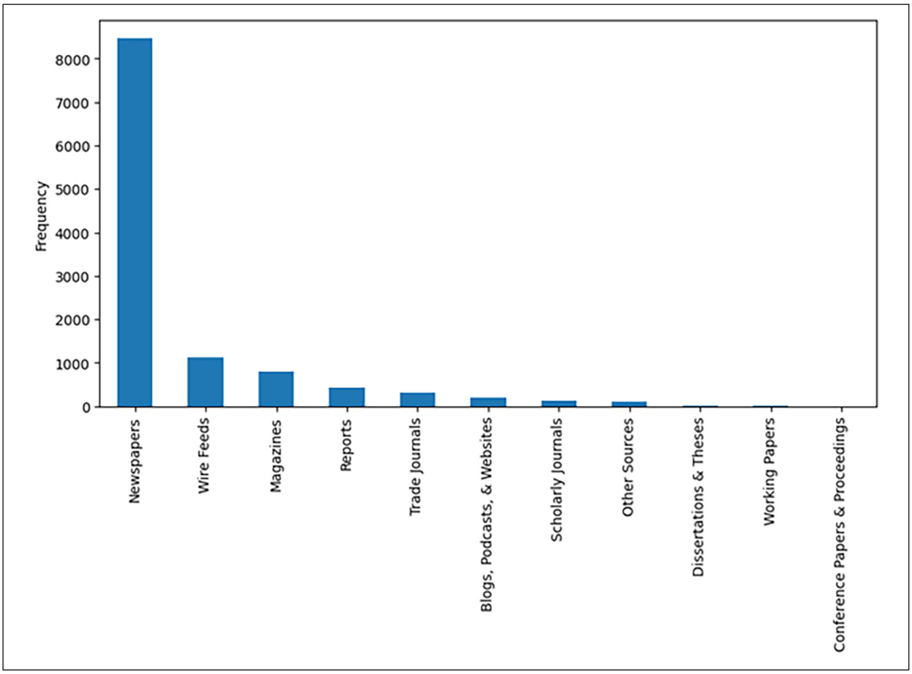

Figure 1. Document Types of Raw Data
Note: Data has been downloaded in ProQuest Central Database (https://www.proquest.com/)

'Korean'. A total of 11,598 documents were identified. However, it is noted that some documents may only mention these countries tangentially, potentially introducing noise into the analysis. The second and third plots focus specifically on documents with titles containing the keywords "China" and "Korea" respectively, aiming to refine the dataset to more relevant content concerning the two countries. Additionally, the fourth plot highlights the intersection of occurrences where both China and Korea are mentioned, with April and October emerging as months with notably high activity in the dataset.

In our analysis, we opt to focus on documents whose titles specifically mentioned 'China' or 'Korea'. <Figure 5> presents a graph of 6,598 documents deemed suitable for analysis. The decision is based upon the premise that rely solely on documents featuring keywords for only one country could result in skewed information, while exclusively considering documents with co-occurring keywords for both countries might be overly restrictive. Consequently, we aggregate the data to encompass both criteria.

Measurement

Initially, we employed natural language processing (NLP) techniques to extract fundamental information from the documents. Tokenization at the word level, while straightforward, proved to be a valuable method for applying economic analysis. Subsequently, we utilize deep learning techniques, specifically transformer-based models (Vaswani et al., 2017), to conduct sentiment analysis. This approach allow us to automatically gauge the economic sentiment between the two countries, offering insights into the underlying perceptions and attitudes present in the textual data.

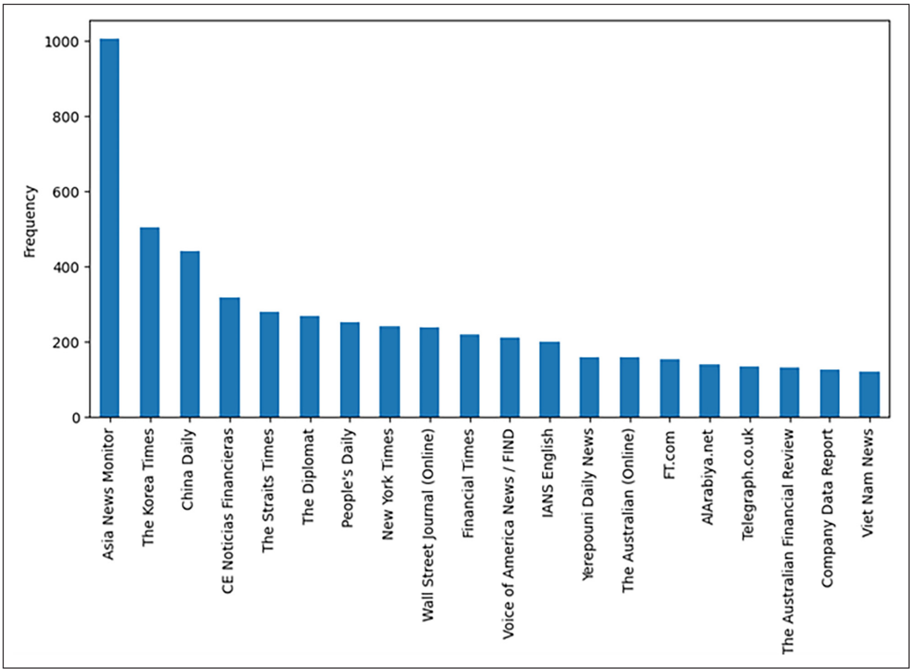

Figure 2. Top20 Publisher by Frequency
Note: Data has been downloaded in ProQuest Central Database (https://www.proquest.com/).

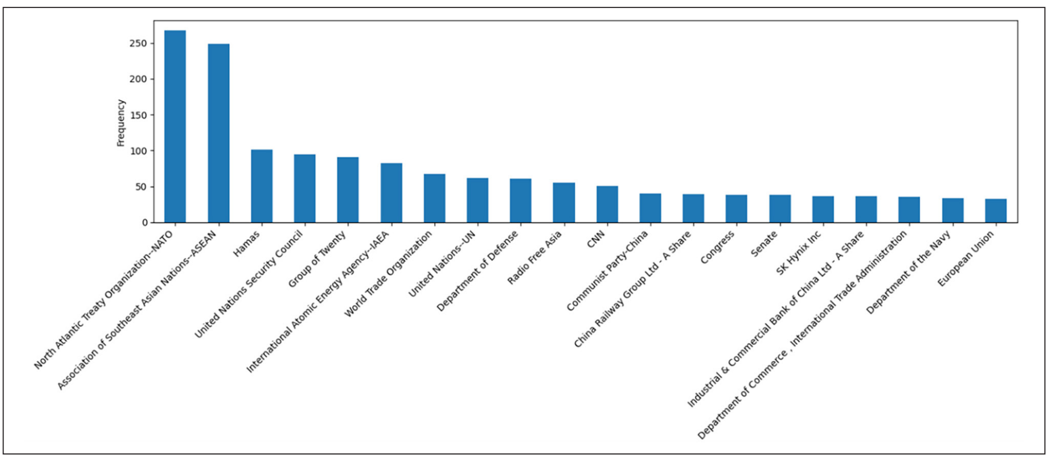

Figure 3. Top20 Publishing Companies by Frequency
Note: Data has been downloaded in ProQuest Central Database (https://www.proquest.com/).

Natural Language Processing

The document titles have been tokenized to separate them into individual words. It means that a title such as “China slams IAEA’s nod for Japan’s plan” has been broken down into “China,”

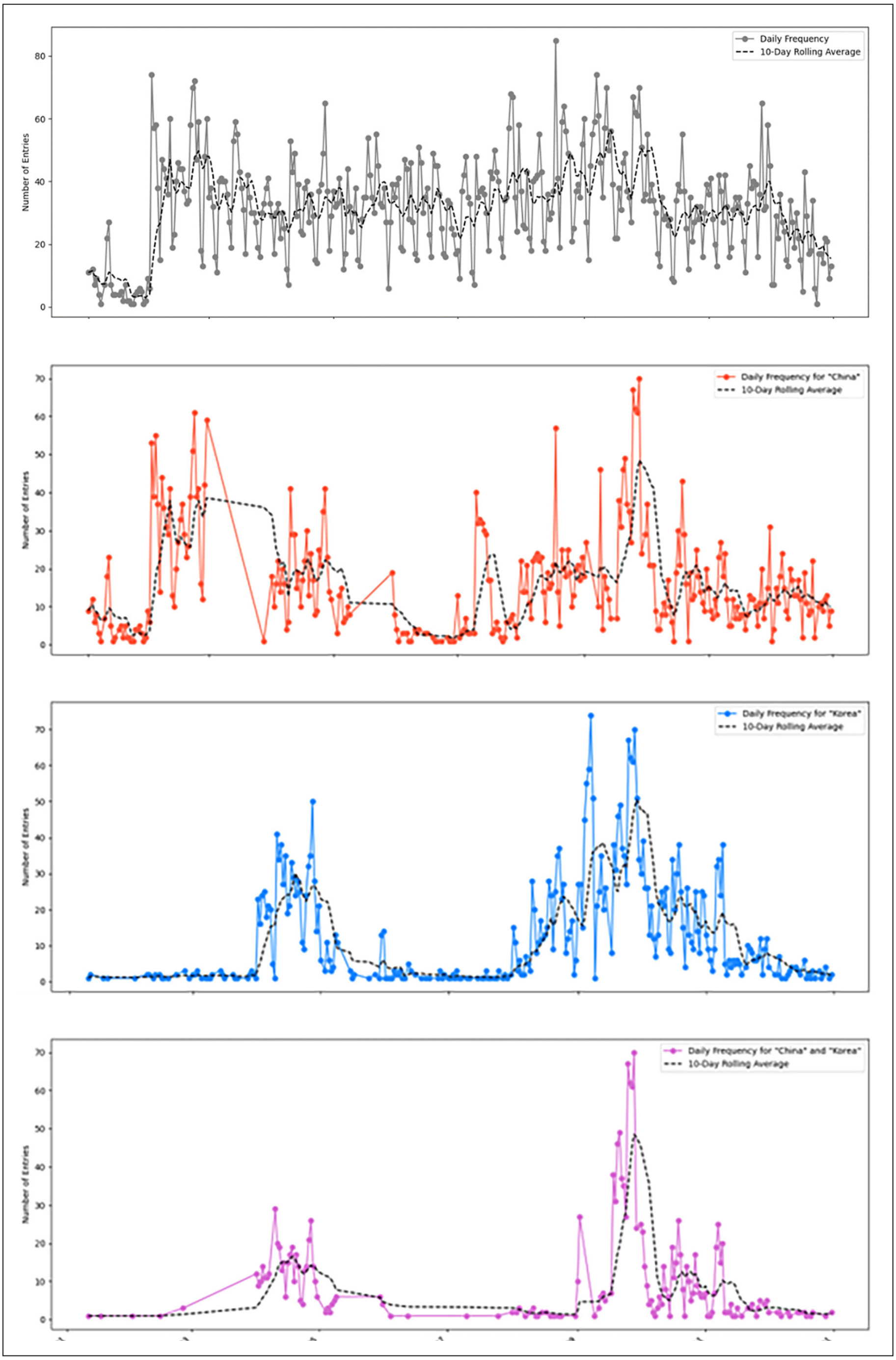

Figure 4. Frequency of Document Entries in 2023

Note: The dataset consists of 11,598 documents. Out of these, 3,469 articles mention "Korea", while 4,664 articles reference "China" in their titles. Additionally, 1,535 articles contain references to both "China" and "Korea" in their titles.

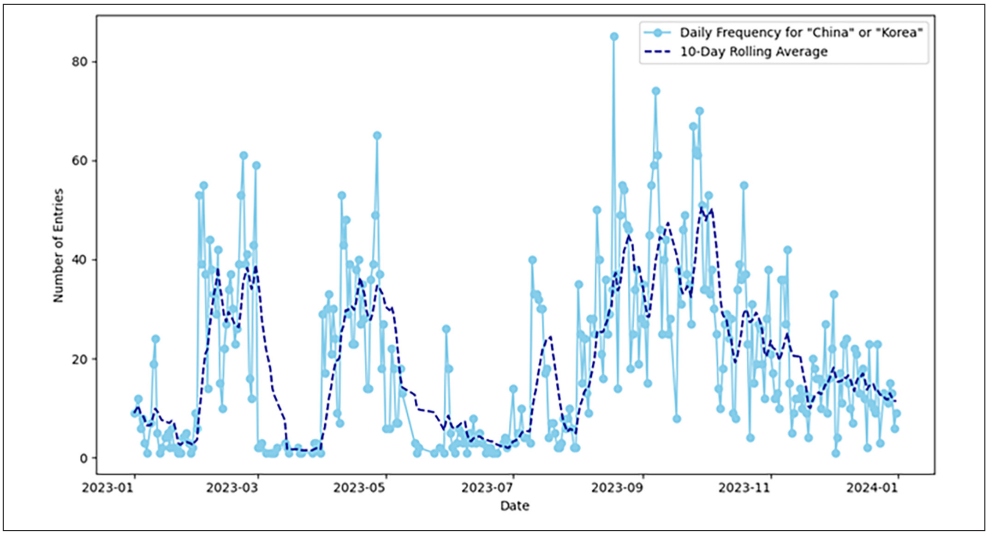

Figure 5. Frequency of Document Entries for China or Korea
Note: In the dataset, there are 6,598 articles that mention either "China" or "Korea" in their titles.

"slams," "IAEA," "nod," "Japan," and "plan." And then, each title has been split into keywords, and the monthly frequency of each keyword has been calculated. This provides useful information about the frequency of certain topics. In Table 1, the top 10 keywords for each month in 2023 are listed with their corresponding frequency values. For example, in January '23', "Russia" appeared 9 times, "trade" appeared 7 times, and "Foreign" appeared 7 times. The note at the bottom of the table explains that common terms such as "mr.," "said," "would," "one," "could," "new," "China," "Korea," "says," and other similar generic keywords have been excluded manually. It is important because it ensures that the frequency count reflects more meaningful data by removing less informative words. By analyzing the table, we can observe that some keywords are consistently prominent across several months (e.g., "Russia," "trade," "Biden"), which may indicate ongoing themes or issues relevant during that time. Other keywords may reflect events or discussions specific to a particular month (e.g., "Antidumping" in May '23').

The presence and frequency of certain keywords can provide insights into the geopolitical or economic discourse during the year 2023, and this table is likely a part of a larger study aiming to analyze trends, sentiments, or topics of interest in relation to the keywords and the context in which they were used.

Sentiment Analysis with Deep Learning

Our approach to deepening the textual analysis for discerning the mood surrounding bilateral issues is indeed methodologically sound. Economic texts often present a challenge for sentiment analysis mainly due to their complexity and the specialized language used, which typical pre-trained models may not accurately interpret. As highlighted by Kim et al. (2023), the intricacies involved in economic texts necessitate more than a general understanding that pre-trained models provide.

Liu et al. (2021) and Gössi et al. (2023) have addressed this challenge by updating and refining the BERT language model specifically for economic texts, resulting in what you refer to as the

Table 1. Top10 reference of Keywords by Monthly

Month Year	Keyword1	Keyword2	Keyword3	Keyword4	Keyword5	Keyword6	Keyword7	Keyword8	Keyword9	Keyword10
Jan-23	Russia,9	trade,7	Foreign,7	ASEAN,7	war,6	relations,6	Biden,6	Taiwan,6	ties,6	coming,5
Feb-23	Russia,71	Taiwan,50	trade,45	war,39	Xi,37	Biden,35	Foreign,32	ties,30	military,27	foreign,26
Mar-23	Xi,30	Biden,23	REGION,23	war,22	trade,21	Games,20	Taiwan,19	Russia,15	NATO,15	exports,15
Apr-23	Russia,133	ties,44	Kim,40	military,38	summit,36	Foreign,35	Biden,28	amid,28	Taiwan,26	nuclear,24
May-23	Duty,57	Determination,54	Antidumping,46	Taiwan,34	Certain,34	Preliminary,33	Final,31	Steel,30	Review,30	Russia,27
Jun-23	Foreign,28	Russia,28	trade,27	Games,23	war,21	water,20	security,18	ASEAN,18	Biden,18	Kim,16
Jul-23	Russia,40	Games,36	Foreign,34	Biden,30	exports,28	trade,27	war,22	nuclear,22	Xi,21	foreign,19
Aug-23	Russia,101	Biden,45	Foreign,41	military,41	Kim,39	nuclear,37	Xi,36	ties,34	war,34	Taiwan,33
Sep-23	Russia,88	Market,68	Biden,55	American,54	Aired,50	ET,50	Kim,41	Taiwan,39	ties,38	Investment,34
Oct-23	Bank,99	Russia,78	quarter,61	Share,44	Agricultural,39	Industrial,39	Commercial,39	Market,32	KOREA,31	nuclear,31
Nov-23	bit,55	Russia,54	Brief,54	Taiwan,38	Summit,22	MOTIE,20	amp,18	Release,18	Foreign,17	Xi,16
Dec-23	Russia,36	Games,28	Biden,27	Xi,26	ties,25	Foreign,23	Kim,18	War,17	Taiwan,16	nuclear,14

Note: Each value corresponds to a "Keyword" and its "Frequency". This result has been manually refined by excluding common terms such as 'mr.', 'said', 'would', 'one', 'could', 'new', 'China', 'Korea', 'says', and other similar generic keywords.

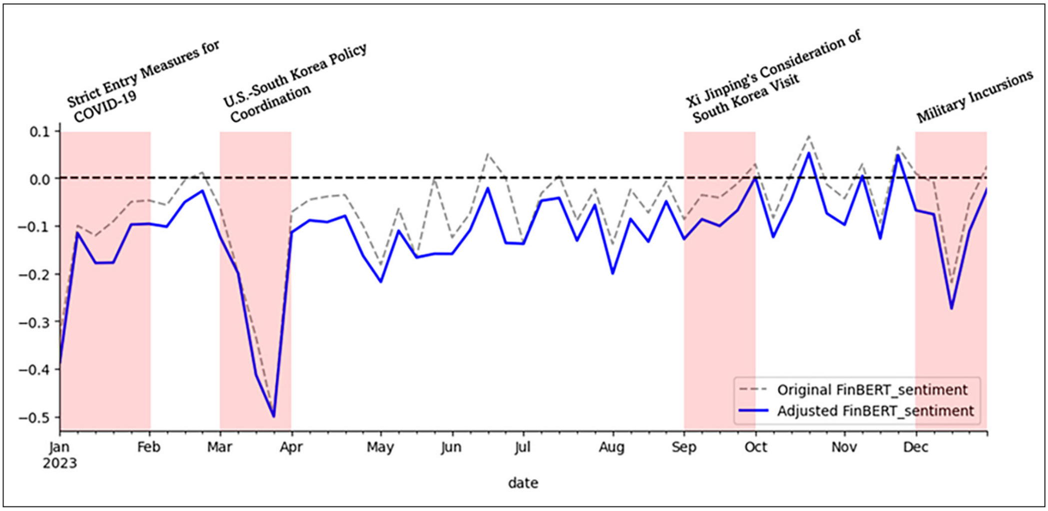

Figure 6. Weekly Sentiment Trends in 2023

Note: The adjusted FinBERT sentiment scores are calculated by deducting the impact of negative words by 'war', 'nuclear', 'military', and 'Taiwan'. Consequently, these adjusted scores are lower than the original FinBERT sentiment values. The shaded red areas seem to highlight periods of volatility or significant changes in sentiment regarding political issues.

FinBERT-FOMC model. BERT, or Bidirectional Encoder Representations from Transformers, is a transformer-based machine learning technique for natural language processing pre-training. The original BERT model is trained on a large corpus of text and then fine-tuned for specific tasks. However, economic texts require a model that is fine-tuned on a relevant corpus that captures the nuances of economic language and sentiment.

The FinBERT-FOMC model the previous studies applied has been specifically fine-tuned for complex economic texts, which likely includes Federal Open Market Committee (FOMC) statements or similar materials. The FOMC statements are known for their impact on financial markets and contain rich economic language that can be essential for a model that aims to analyze economic sentiment.

Using the FinBERT-FOMC model, the sentiment analysis can more accurately capture the subtleties of economic discourse, allowing for a nuanced understanding of the sentiment in economic texts regarding China and Korea. By applying this model, we can determine whether the sentiment is positive, negative, or neutral, which can be particularly useful for gauging market sentiment or the overall mood of bilateral economic relations.

<Figure 6> depicts the weekly average sentiment scores for news data in the year 2023, comparing two sets of results obtained from sentiment analysis using the FinBERT model. Dashed line This line represents the sentiment scores obtained from the original application of the FinBERT model (Gössi et al., 2023) on the dataset. Solid Line (Adjusted FinBERT Sentiment) shows the sentiment scores after adjusting the original FinBERT results by stressing the influence of certain negative words, specifically 'war', 'nuclear', 'military', and 'Taiwan'.

The graph shows fluctuations in sentiment throughout the year with both lines following a somewhat similar pattern—this indicates that overall trends in sentiment are preserved even after the adjustment for negative words. However, the adjusted sentiment line is consistently lower than the original sentiment line, which means that once the identified negative terms are discounted, the overall sentiment becomes more negative on average. The observation by Kim

Table 2. Main issue between China and Korea in 2023

Month	Main Issue or Event	Brief Description	URL
January	COVID-19 related issues	China suspended issuing short-term visas in South Korea (and Japan) as a retaliatory measure against countries that required negative COVID-19 tests from Chinese travelers.	https://www.reuters.com/world/china/covid-wave-past-its-peak-many-parts-china-state-media-2023-01-10/
February	-	No specific issue highlighted.	-
March	U.S.-South Korea Policy Coordination	Discussion on policy coordination towards China on democratic values and human rights.	https://www.cfr.org/blog/us-south-korea-policy-coordination-toward-china-democratic-values-and-human-rights
April	-	No specific issue highlighted.	-
May	Diplomatic Spat	A diplomatic exchange following the Taiwan Strait comments marked serious diplomatic discourtesy.	https://asiatimes.com/2023/05/china-s-korea-deepening-suspicions-limited-diplomacy/
June	-	No specific issue highlighted.	-
July	Fukushima Water Release Controversy	Controversy arose over Japan's plan to release treated wastewater from the Fukushima nuclear power plant. China was seen as potentially using this issue to divide Seoul and Tokyo, amidst protests in South Korea against the plan.	https://www.voanews.com/a/experts-china-sees-fukushima-water-release-as-tool-to-divide-seoul-and-tokyo/7170792.html
August	-	No specific issue highlighted.	-
September	Xi Jinping's Consideration of South Korea Visit	Xi Jinping expressed serious consideration of visiting South Korea, aiming to support peace and security on the Korean Peninsula.	https://www.reuters.com/world/china/china-willing-work-with-south-korea-ahead-summit-with-japan-xi-2023-09-23/
October	Protest over North Korean Defectors	South Korea protested to China over the repatriation of North Korean defectors.	https://www.scmp.com/news/china/diplomacy/article/3237876/seoul-makes-rare-protest-china-over-repatriation-north-korean-defectors
November	Economic Cooperation Mechanism	China and South Korea agreed to establish a mechanism on practical economic cooperation.	https://www.reuters.com/world/asia-pacific/china-south-korea-establish-mechanism-practical-economic-cooperation-2023-11-15/
December	Military Incursions	Chinese and Russian warplanes entered South Korea's air defense zone without notice, leading to a South Korean military protest.	https://www.scmp.com/news/china/military/article/3245084/south-korea-scrambles-fighters-after-chinese-and-russian-warplanes-enter-air-defence-identification

(2023) that a negativity-focused sentiment score may yield better predictive power of economic conditions is noteworthy. This perspective is grounded in the theory that negative news can have a disproportionate impact on market sentiment and investor behavior, often resulting in more significant and rapid market reactions compared to positive news. This phenomenon is sometimes referred to as the "negativity bias" in the field of behavioral economics, where negative events or emotions have a greater effect on an individual's psychological state and processes than neutral or positive things (Kim, 2023).

When applying sentiment analysis, especially in the context of economic forecasting or market analysis, incorporating a weighting scheme that emphasizes negative sentiment could therefore improve the model's ability to forecast economic downturns or market volatility. This approach would be particularly relevant if historical data supports the premise that markets respond more vigorously to negative news.

However, it is also important to consider that an overemphasis on negative events can lead to a skewed perspective if not balanced by an understanding of positive developments and their potential impact. A comprehensive sentiment analysis should consider the full spectrum of news sentiment to provide a balanced view of market dynamics.

Inference

When discussing the main issues reflected by a sentiment score, especially in the context of economic relations between two countries, it is important to consider various dimensions that can be captured by news sentiment. These dimensions often include changed in political events, economic policies, trade relations, and other significant developments. Here's how these issues can be reflected in a sentiment score (See Table 2):

Issue on January: *Association with COVID-19*

The issue at hand concerns the World Health Organization's challenge in assisting China with managing the risks of a COVID-19 surge, hindered by a lack of data from China. As the country reopened after three years of isolation and in anticipation of the Lunar New Year travel rush, China's response included imposing transit curbs for South Korean and Japanese nationals. This action escalated diplomatic tensions and potentially complicated economic relations, as both South Korea and Japan had implemented strict entry measures for travelers from China. This context may have contributed to the negative sentiment reflected in the FinBERT sentiment score, where it was observed to be around -0.4 points, indicating a predominantly negative economic outlook at the time.

Issue on March: *U.S.-South Korea Policy Coordination*

The issue under discussion is the virtual workshop between the U.S. and South Korea. The workshop aims to talk about policy coordination towards China, with a focus on democratic values and human rights. The discussion explores South Korea's foreign policy under President Yoon Suk Yeol, emphasizing a values-based approach and international liberal norms. This approach aligns with the U.S. to protect the rules-based order amid challenges from authoritarian regimes. The FinBERT sentiment score shows the lowest score of -0.5 points. If reflecting this topic, it could show a dip due to the negative connotations associated with the challenges of upholding human rights and democratic values against opposition from authoritarian stances.

Issue on September: *Xi Jinping's Consideration of South Korea Visit*

The article reports that Chinese President Xi Jinping has expressed a willingness to visit South Korea, according to Yonhap news agency. This is seen as part of efforts to support peace and security on the Korean Peninsula. This intention was communicated as both countries are looking to promote a strategic partnership and comes ahead of a trilateral meeting scheduled in Seoul with China, Japan, and South Korea. The discussions are meant to set the stage for a summit between the three countries, which would be the first in four years.

In terms of the FinBERT sentiment score, this development could potentially be reflected in a positive uptick, as it indicates a willingness for diplomatic engagement and cooperation, which are generally seen as positive by markets and could improve economic confidence between the countries involved. If the FinBERT sentiment score shows a rise above zero in response to this news, it would suggest that the markets are responding favorably to these diplomatic advances.

Issue in December: *Military Incursions*

The incident you referred to involved South Korean military scrambling fighter jets after detecting an incursion into its air defense identification zone (ADIZ) by Chinese and Russian military aircraft. This event occurred on December 14, 2023, and the South Korean Joint Chiefs of Staff reported that two Chinese and four Russian aircraft had entered the ADIZ without prior notice, remaining there for about 17 minutes. These aircraft did not enter South Korean territorial airspace but flew within the air defense identification zone, which is a designated area of controlled airspace extending beyond a country's territory to give the country more time to respond to potentially hostile aircraft. The FinBERT sentiment score (-0.3 point) would likely reflect a negative sentiment following such an event, considering it involves military activity and potential geopolitical tension. The index, designed to analyze complex economic texts, could interpret this incident as one that might create uncertainty or concern in the market, potentially affecting investor sentiment negatively.

Findings and ways ahead

Abundant Document Data Representing Economic Sentiment

The substantial volume of documents, including newspaper articles, wire feeds, and reports, has been a rich source of information for gauging economic sentiment. The frequency of keywords and the sentiment scores derived from these documents have given a detailed picture of the economic narrative and its fluctuations over time. However, this observation also raises the question of causality: does the sentiment reflected in the media influence the economic relations and market behaviors, or do economic conditions and events shape media sentiment?

Quantitative Data Generation

The application of natural language processing and sentiment analysis techniques to news articles and reports has provided quantitative data regarding the bilateral sentiments between the two countries. This approach has allowed for a more objective and data-driven understanding of the economic sentiment, political climate, and cultural exchanges that characterize the relationship between the two nations.

Ways Ahead

Enhanced Sentiment Analysis Models: Given the findings, it may be beneficial to further refine sentiment analysis models, like FinBERT, to better capture the nuances of economic language and context-specific sentiment. Enhancing these models could involve incorporating more domain-specific training data or adjusting model parameters to focus on certain aspects of sentiment, such as the predictive power of negative sentiments.

Broader Data Inclusion: To gain a more comprehensive understanding, future research could expand the dataset to include additional types of documents or data from social media platforms, which could provide insights into the public's perception and sentiment.

Cross-Validation with Economic Indicators: The sentiment score results can be cross-validated with actual economic performance indicators of the two countries to evaluate the predictive power of the sentiment analysis and refine the methodology accordingly.

Conclusion

This study highlights the importance of Natural Language Processing (NLP) and sentiment analysis in interpreting media sentiment, especially regarding China and Korea. The study reveals complex sentiment patterns that reflect the geopolitical and economic dynamics between the two nations by examining datasets. Using transformer-based models for sentiment analysis represents a significant advancement, allowing for more nuanced sentiment detection.

The correlation between sentiment analysis results and actual geopolitical events proves the effectiveness of NLP methodologies and underscores their potential for predictive analytics in international relations. This research suggests that media sentiment could serve as a leading indicator for shifts in geopolitical stances and economic policies. This opens new avenues to understanding the impact of media narratives on public perception and foreign policy.

The study recommends an integrated approach to media analysis, combining quantitative NLP techniques with qualitative assessments to accurately capture national sentiment and its implications. As geopolitical landscapes change, analyzing and interpreting media sentiment becomes crucial for policymakers, analysts, and scholars to anticipate and respond to international developments.

In conclusion, this research provides valuable insights into media sentiment dynamics towards China and Korea, showcasing the transformative potential of NLP and sentiment analysis in international relations research. Applying these methodologies promises to deepen our understanding of global media narratives, offering a potent tool for navigating the complexities of international diplomacy and economic relations.

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Generative AI or AI-assisted technologies were not used in any way to prepare, write, or complete essential authoring tasks in this manuscript.

Conflict of Interests

The author(s) declare that there is no conflict of interest.

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