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# Topic Analysis of Foreign Policy and Economic Cooperation: A Text Mining Approach

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## Abstract

***Purpose*** –International diplomacy is key for the cohesive economic growth of countries around the world. This study aims to identify the major topics discussed and make sense of word pairs used in sentences by Chinese senior leaders during their diplomatic visits. It also compares the differences between key topics addressed during diplomatic visits to developed and developing countries.

***Design/methodology*** – We employed three methods: word frequency, co-word, and semantic network analysis. Text data are crawling state and official visit news released by the Ministry of Foreign Affairs of the People's Republic of China regarding diplomatic visits undertaken from 2015–2019.

***Findings*** – The results show economic and diplomatic relations most prominently during state and official visits. The discussion topics were classified according to nine centrality keywords most central to the structure and had the maximum influence in China. Moreover, the results showed that China's diplomatic issues and strategies differ between developed and developing countries. The topics mentioned in developing countries were more diverse.

***Originality/value*** – Our study proposes an effective approach to identify key topics in Chinese diplomatic talks with other countries. Moreover, it shows that discussion topics differ for developed and developing countries. The findings of this research can help researchers conduct empirical studies on diplomacy relationships and extend our method to other countries. Additionally, it can significantly help key policymakers gain insights into negotiations and establish a good diplomatic relationship with China.

**Keywords**: Diplomatic Visits, Foreign Policy, Text Analysis, Sematic Network Analysis, Word Frequency
**JEL Classifications**: F59, O53, P41

## 1. Introduction

Economic diplomacy has gradually become an important component of China's overall diplomacy owing to deepened economic globalization and an increase in China's economic power. Recently, its appearance in official Chinese documents has been increasing (Men, 2013). Several researchers have also examined the relationship between Chinese economics and diplomacy. They have demonstrated that China's diplomatic activities promote economic cooperation, primarily by employing econometrics using cross-sectional and panel data (Beaulieu et al., 2020; Davis et al., 2019; Desbordes, 2010; Lin et al., 2017; Zhang et al., 2014). They considered diplomatic visits, negative government events, daily conflict events, embassies,

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consulates, and the Export promotion agencies (EPA) and investment promotional agency (IPA) offices to represent diplomatic activities. Consequently, most current studies on economic diplomacy employ a quantitative method and lack qualitative analysis for objective interpretation.

Communication technology development facilitates information access and provides opportunities to collect unstructured data from various sources, such as social media and official websites. Moreover, advances in natural language processing have been efficiently used for qualitative analysis. Word Cloud is a representative technique for analyzing unstructured text data that extracts processed words (nouns or adjectives) from unstructured text data and visualizes them by evaluating their frequency of appearance. Therefore, it can be used to easily identify important and high-interest topics. Additionally, co-word analysis has been proven to be effective in revealing latent connotations and evolutionary venation (Alcaide–Muñoz et al., 2017; Huang et al., 2014; Huang et al., 2015). Co-word analysis can be used to construct a co-word network by calculating the co-occurrence between words (Assefa & Rorissa, 2013). Then, by using network indicators (Zhao et al., 2018) and visualization (Khasseh et al., 2017), we can explore the deeper meaning of the text content via topic word centrality indicators (Hu et al., 2018), correlation network indicators (overall and individual), topic community detection (direction), and mapping topic correlation structures (Wei et al., 2020). Co-word analysis and related methods can be employed to explore the major topics and semantic structure (Cobo, López-Herrera, et al., 2011; Cobo, López-Herrera, et al., 2011) from discussions that occur during diplomatic visits of senior Chinese leaders.

Recently, research on using text analysis in political science has been increasing (Beelen et al., 2017). For instance, Park et al. (2019) used social media to assess the practices and effectiveness of digital diplomacy between Korea and Japan by linking international relations literature, a social network approach, and topic modeling. Wei et al. (2020) used parliamentary texts comprising records of discussions on domestic and international affairs reflecting national attitudes and development trends in foreign relations between UK and China. However, detecting related economic diplomacy texts to obtain a deeper understanding of economic and diplomatic strategies is not prevalent. Moreover, compared to liberal democracies, China is characterized by a high level of opacity and secrecy, with considerable restrictions on access to relevant information. This is prominent in their practice of regulating citizens' access to the Internet and strict cyber surveillance of content posted and shared on social networks (Fernandes, 2021).

Owing to the aforementioned difficulties, some studies have adopted qualitative analysis using official Chinese documents (Fernandes, 2021). In particular, the official press releases made by the Ministry of Foreign Affairs (MFA) of the People's Republic of China (PRC) include important core words regarding China's foreign policies and future behaviors. For instance, the Belt and Road Initiative (BRI) has been China's most important foreign policy, which was unveiled by the president in 2013 during his visits to Kazakhstan and Indonesia. Subsequently, the premier promoted it during his official visits to Asia and Europe. From this viewpoint, the Chinese leaders' speeches during these diplomatic trips hid valuable information. The press releases regarding Chinese senior leaders' diplomatic visits comprised unstructured text that contained millions of information pieces. Therefore, interpreting the speech topic distribution of diplomatic trips is beneficial for understanding diplomatic situations and foreign policy, which can facilitate diplomatic strategy planning.

Thus, this study aimed to understand the major topics discussed and make sense of word pairs from press releases of Chinese diplomatic trips. It also compared the key topics discussed during diplomatic visits to developed and developing countries. To achieve this, we employed three methods: word frequency, co-word, and semantic network analysis. Text analysis was performed by crawling news regarding senior Chinese leaders' diplomatic visits between 2015 and 2019, released by the MFA of the PRC, with the following research questions (RQs): 1) What were the major topics of discussion when senior Chinese leaders made diplomatic visits? 2) What is the context of the words related to Chinese senior leaders' diplomatic visits to other countries? 3) What is the correlation structure of topic words related to developed and developing countries?

This study offers valuable insights into the objective interpretation of official announcement texts and can help discover concealed topics discussed during Chinese diplomatic trips. Therefore, this study provides substantive research questions for researchers studying Chinese economic diplomacy and foreign policy. Moreover, it makes significant contributions to foreign policymakers, who are perhaps the most important political institutions in other countries, such that they can use the database provided in this study to acquire insights into negotiations and establish a good diplomatic relationship with China.

The remainder of this paper is organized as follows. Section 2 reviews previous studies. Section 3 describes the research framework, data collection, and preprocessing methods. Section 4 discusses the results of the text analysis. Finally, the conclusions, limitations, directions for future research are summarized in Section 5.

## 2. Literature Review

### 2.1. Diplomatic Visits and Political and Economic Cooperation

The term "economic diplomacy" appears regularly in scholarly papers and official documents of China (Okano-Heijmans, 2011). Hence, it is evident that economic diplomacy has gradually become an important component of China's diplomatic activity (Fernandes, 2021). Nitsch (2007) pointed out that the United States, France, and Germany recognize political visits by heads of state as the highest form of diplomatic exchange and contact. Aleksanyan et al. (2021) confirmed that corporations from visiting countries are more likely to acquire corporations in countries hosting their visits. Afman and Maurel (2010) showed that "economic diplomacy is associated with higher exports, suggesting that export promotion by creating permanent missions is effective in increasing trade with transition countries. Moreover, efforts to promote investments can increase foreign direct investment (FDI) inflows to developing countries (Harding & Javorcik, 2007). Desbordes (2010) reported that diplomatic relations affect the amount of FDIs made in developing countries. Bergeijk et al. (2011) demonstrated that diplomatic representation is not a relevant trade-enhancing factor for trade within the countries comprising the Organization for Economic Co-operation and Development; however, it is significant for promoting bilateral trade relationships in developing countries.

China's economic diplomacy has experienced two stages: the previous one was that economy promotes diplomacy, whereas the current one is that diplomacy promotes economy (Ke, 2011). Lin et al. (2017) found that Chinese politician state visits to African countries significantly increased official aid and exports to those countries. Beaulieu et al. (2020) suggested that state visits increase trade between China and its trading partners two or three years after the visit. Sun and Liu (2019) showed that the establishment or upgradation of partnerships has a positive effect on Chinese firms' decisions on outward FDI (OFDI), at least in the short term. They also elaborated that the increase in OFDI is concentrated in host countries with higher political risks, such as developing, neighboring, and BRI countries, which is consistent with China's diplomatic focus. Additionally, Kang and Jiang (2012) and Davis et al. (2019) investigated institutional factors, diplomacy by corporate characteristics, and political and economic relations in China and India.

In summary, early studies investigated bilateral political indicators based on event data to explain bilateral economic activities (trade or investment) and primarily employed cross-sectional analyses (Nigh, 1985; Polachek, 1980; Pollins, 1989). Some researchers have extended the existing literature and employed more specific tools of economic diplomacy as independent variables (including state visits, official visits, embassies, consulates, and EPA and IPA offices) using panel data (Afman & Maurel, 2010; Aleksanyan et al., 2021; Beaulieu et al., 2020; Bergeijk et al., 2011; Davis et al., 2019; Desbordes, 2010; Harding & Javorcik, 2007; Kang & Jiang, 2012; Lin et al., 2017; Nitsch, 2007; Sun & Liu, 2019; Zhang et al., 2014). Specifically, they employed different-in-different, ordinary least squares, fixed effect, random effect, Poisson pseudo maximum likelihood, and two-stage least squares methods. Moreover, news reports of historical diplomatic events and official documents constitute important data that can be used to analyze diplomacy and economics. The Chinese government never openly stated its practice of economic diplomacy before 2004 (Ye and He, 2004), whereas it has appeared more frequently in their official documents in recent years (Men, 2013). Wei et al. (2020) used parliamentary documents to reflect the characteristics and patterns in foreign relations between UK and China. Furthermore, Yakop and van Bergeijk (2011) proposed that the effects of economic diplomacy differ between different country groups according to different income levels. That means diverse country groups may differently emphasize the major topics.

## 2.2. Text Mining for Diplomatic Relations

The digitized corpus has the potential for new advances within other areas of social sciences and humanities, and in varied disciplines, such as political science, communication, psychology, linguistics, history, economics, and sociology. In particular, political scientists are interested in using text mining to understand the correlation networks established using particular words. Some scholars have attempted to analyze text using social community or parliamentary documents (Park et al., 2019; Park & Lim, 2014; Wei et al., 2020). Park et al. (2019) used social network analysis to evaluate digital diplomacy. Jiang et al. (2016) selected the 150 most frequently occurring words in international news coverage and performed semantic network analysis to investigate the news frames of international news coverage between the U.S. and China, as well as the framing dynamics. Chowdhury and Koya (2017) calculated the term frequency in four key United Nations policy documents and conducted a thematic analysis of sustainable development. Wei et al. (2020) conducted a co-word analysis to understand the characteristics of foreign relations topics between UK and China. They presented text analysis frameworks to acquire insights into diplomacy and topics of foreign relations. Jiang et al. (2018) employed a semantic network analysis based on frequently occurring words to investigate the dynamic co-evolution of peace frames embedded in news coverage. Huang et al. (2018) stated that the policy change analysis framework comprises data collection, pattern identification, network construction, eigenvector centrality calculations, and topic change analysis based on shifts in network centrality.

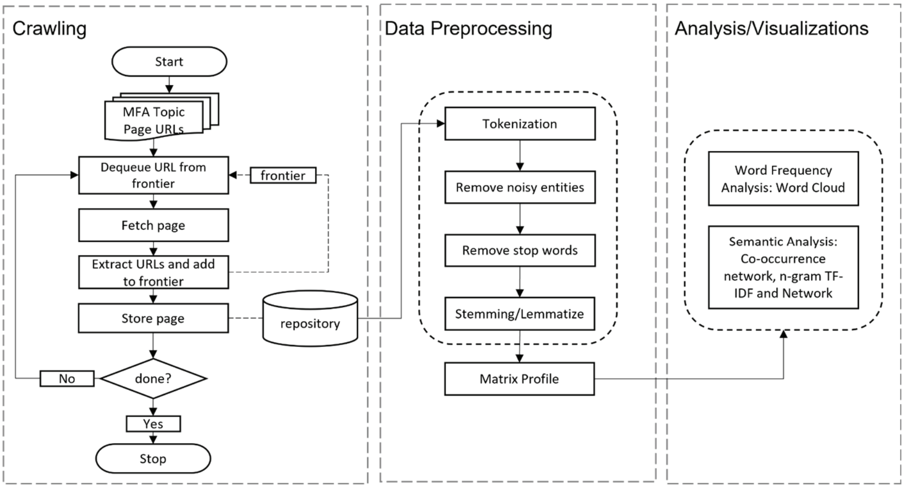
Consequently, economic diplomacy news is important for analyzing China's economic diplomacy and foreign policy, because it records direct and practical information regarding diplomatic activities. However, the analysis of these data is limited, and the distribution and exploration of economic diplomacy topics are inadequate. Text analysis based on linguistic elements allows researchers to explain the structure and evolution of a field, and the general workflows proposed by the aforementioned scholars provide useful references. Therefore, this study attempted to present Chinese economic diplomacy and foreign policy directions via the network structure of keywords extracted from economic diplomacy news released by the MFA of the PRC.

## 3. Method and Data

The proposed framework comprises two components: data collection and analysis. The proposed framework is illustrated in Fig. 1. Data collection methods include crawling and data preprocessing (or data cleaning). The detail explanation present in the part 3.1 and 3.2. Data analysis methods include word frequency, co-words, and semantic analysis. Data analysis detail propose in the part 3.3.

The programming environment used in this study included Windows 10, Python 3.8.5, PyCharm 2020.3.2 (Community Edition), R version 4.0.5, and RStudio version 1.4. We used the Xlwt and Beautiful Soup libraries in Python, and dplyr, tidyr, widyr, tidytext, stringr, tm, ggplot2, tidygraph, ggraph, igraph, and wordclous packages in R. Some packages require installation prior to use. The libraries could be run after installation.

**Fig. 1.** Overview of the proposed framework




### 3.1. Data Collection

This section describes the methods used to crawl the news information. Two main types of data were used: primary and secondary. Primary data are collected for specific studies through surveys, interviews, field observations, and experiments. However, this method is expensive and time-consuming. Secondary data are collected from various sources, such as newspapers, journals, and annual reports. We obtained secondary data from official announcements of the state and official visits. It was crawled from the website of the MFA of the PRC (collected on February 1, 2021), which is an official website (https://www.fmprc.gov.cn/mfa_eng/) that provides data regarding Chinese foreign policies, foreign activities, press, and media services (see Fig. 2). The following steps were employed for crawling:

**Step 1:** Obtain the header information of the web page.
**Step 2:** Fetch the webpage and initiate content extraction. The request.get() function returns the response information based on the URL connection information.
**Step 3:** Convert the data into string types. "".text" converts the response object into a string type.
**Step 4:** The URLs are extracted and added to the frontier. The find_all() function searches for all "a" tags under the "('div', {'class': 'newsLst_mod'})." Element.get('href') obtains each page's last_shtml.
**Step 5:** Cycle through Steps 2 to 4 until no more pages remain.
**Step 6:** Filter and obtain the required information. The find_all() function searches for all "('p', {'style': 'FONT-SIZE:14px; FONT-FAMILY: arial'})" tags under the "('div', {'class': 'content'})" tag;
**Step 7:** The data are converted into the.csv format and saved directly to the local computer.

This program was used to successfully crawl 1,271 news documents.

**Fig. 2.** Website of the MFA of the PRC (Diplomatic activities list)

## 3.2. Data Preprocessing

This section describes natural text preprocessing that eliminates noisy entities and stop words, and performs stemming. After the data crawl via Python is completed, the data are preprocessed in the R program. The detailed steps of text preprocessing are as follows:

**Step 1:** Tokenization. A document is treated as string text, and tokenization is the process of splitting text into tokens. After collecting the context data, the text is split into words (list type).
**Step 2:** Stop word removal. Some English words that are common and do not add much value are removed, such as "a," "I," "the," "in," and "of." A total of 571 stop words were included, which are listed in the system for the mechanical analysis and retrieval of text information retrieval system (Lewis et al., 2004; Li et al., 2021; Shin et al., 2018).
**Step 3:** Stemming. Stemming converts different word forms into similar standard forms. It was performed for morphologically identical and semantically large, undifferentiated entries, such as "cooperation," "cooperative," "cooperating," "cooperated," "cooperatives," and "cooperates." However, semantically distinct entries, such as "developed" and "developing," were retained as separate entries.

It is crucial to establish text data. In case of insufficient processing, the process was resumed, and cleaning was repeated. After the data preprocessing task was completed, the data were converted into data frames for analysis. Consequently, 292,743 words and 8,162 keywords were identified.

## 3.3. Analysis Measurement

### *3.3.1. Word Frequency Analysis*

Word frequency indicates the popularity of a term or keyword. Frequently used words indicate the emphasis of a particular news article; hence, frequency must be first determined when analyzing text. In this study, word frequency analysis was performed via word clouds and networks. First, the entire news article was visualized in a word cloud, and then a word cloud and co-occurrence network were visualized through country classification to identify core topics.

A word cloud is used to analyze the number of times a word occurs in an article. It is created using different font sizes and colors depending on the word frequency, which makes it easy to identify the number of words used. However, the meaning of some words can be unclear, and such misunderstandings can result in misinterpretations of passages. Therefore, we also performed network analysis to identify links among keywords.

### *3.3.2. Co-word Analysis*

Network-based methods are commonly employed to identify the relevance of keywords. The co-word network creates keyword nodes and co-occurrences of keyword edges connecting the nodes. This network property can be leveraged to evaluate keyword nodes (Hu et al., 2018). High node centrality indicates that keywords frequently appear in the text, and high betweenness centrality can determine the number of times words are used together, because keywords function as connections between different subnetworks.

Freeman (1978) suggested three centrality measurement methods for a network: degree centrality, betweenness centrality, and closeness centrality (Freeman, 1978). Degree centrality is defined as the number of direct links between word i and other words. Granovetter (1973) suggested that a nodal degree is proportional to the probability of obtaining resources (Granovetter, 1973). Nodal degree represents the degree to which a node (word) participates in the network, which is the basic concept used to measure centrality. The concept of betweenness refers to how often a word is located on the shortest path between any two other words in the network. The words located on the shortest path between other words play intermediary roles that allow any two words without direct contact to reach each other indirectly. Words with higher centrality are those located at the core of the network. The inverse of the average lengths of the shortest paths to/from all other words indicates the closeness centrality of the network. A higher closeness centrality indicates a greater influence on other words (Lee and Su, 2010). We used the co-occurrence network property to compare keywords by country classification. The following equations were used for these calculations:

$$\text{Degree centrality: } d(i) = \sum_j m_{ij} \tag{1}$$

$$\text{Between centrality: } b(i) = \sum_{j,k=1} \frac{g_{ijk}}{g_{jk}} \tag{2}$$

$$\text{Closeness centrality: } c(i) = \sum_{j=1}^{N} \frac{1}{d_{ij}} \tag{3}$$

where $m_{ij} = 1$ if words *i* and *j* are linked, $g_{ijk}$ denotes the shortest path between words *j* and *k* that contains word *i*, $g_{jk}$ denotes the shortest path between words *j* and *k*, and $d_{ij}$ denotes the shortest path between words *i* and *j*.

### *3.3.3. Semantic Network Analysis*

By analyzing different patterns in a joint word network constructed from a list of keywords, we distinguished meaningful keywords extracted from literature (Ding et al., 2001). However, most centrality metrics are highly correlated with frequency-based methods, wherein semantic implications of the keywords are not considered. Therefore, a semantic-based method is required because semantic analysis is useful for understanding the context of words used in sentences. This section describes the bigram network measurement and term frequency–inverse document frequency (TF-IDF) analysis.

Semantic network analysis is a meaning-centered network approach for examining the relationship between textual components in content based on the co-occurrence of words. The network calculation method is described above. Semantic networks provide tools for generating data through n-gram tokenization, understanding the context of words appearing in news, and providing other words associated with core words.

We expected that visits to developed and developing countries would differ in terms of topic and content. TF is the most commonly employed quantitative analysis method. Therefore, TF-IDF methods (Chang et al., 2021; Salton & Buckley, 1988) have been extended to semantic analysis and quantified using the TF-IDF metric. Specifically, keyword frequency is replaced with semantic unit frequency. This equation can be expressed as follows:

$$TF - IDF = n(i,j) \times \log\left(\frac{n(all)}{n(i,all)}\right) \tag{4}$$

where $n(i,j)$ denotes the TF of word $i$ in corpus $j$, $n(all)$ denotes the number of all documents, $n(i,all)$ denotes the number of words in all documents, and $\log\left(\frac{n(all)}{n(i,all)}\right)$ denotes the IDF of a word.

# 4. Results and Discussion

## 4.1. Status of the State and Official Visits

State and official visits are considered to have the highest expression of friendly bilateral relations between sovereign states. The president made 98 state visits to 69 countries between 2013 and 2019. The premier made 60 official visits to 47 countries during the 2013–2019 period. Tables 1 and 2 list the state and official visits by region and year, respectively. The maximum number of state and official visits were to Asian and European regions. Although the number of annual visits appears consistent, the frequency was higher in the earlier years. Fig. 3 shows a choropleth map of countries visited. Red denotes China and darker shades of blue denote countries with higher frequencies of visits. The most visited country was Russia, with 12 visits, followed by Kazakhstan, Belgium, Germany, and the United States, with 5 visits each. India, Indonesia, Uzbekistan, and France were each visited four times. The state and official visit routes are nearly consistent with the six major economic corridors of the BRI initiative, which shows that state and official visits are partly related to foreign policies.

**Fig. 3.** Choropleth map indicating state and official visits made by Chinese senior leaders between 2013 and 2019

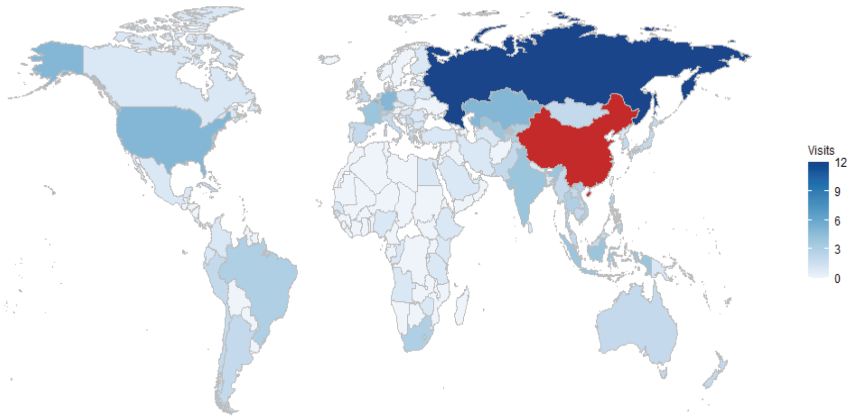


**Table 1.** State and official visits by region between 2013 and 2019

| Region | State Visits | Official Visits | State and Official Visits |
|---|---|---|---|
| Africa | 10 | 4 | 14 |
| Asia | 39 | 23 | 62 |
| Europe | 28 | 24 | 52 |
| Latin America | 13 | 5 | 18 |
| North America | 4 | 2 | 6 |
| Oceania | 4 | 2 | 6 |

**Source:** State and official visit data from 2013–2014 were obtained from Wikipedia (https://en.wikipedia.org/wiki/Main_Page) and other data regarding visits from 2015–2019 were obtained by crawling released news titles from the MFA of the PRC on February 1, 2021.
**Notes:** State visit indicates president's visit; official visit indicates premier's visit; official visits include two working visits (Switzerland-2015; Belgium-2018).

**Table 2.** State visits and official visits by year

| Year | State Visits | Official Visits | State and Official Visits |
|---|---|---|---|
| 2013 | 16 | 9 | 25 |
| 2014 | 18 | 13 | 31 |
| 2015 | 15 | 9 | 24 |
| 2016 | 15 | 9 | 24 |
| 2017 | 8 | 7 | 15 |
| 2018 | 13 | 9 | 22 |
| 2019 | 12 | 5 | 17 |

## 4.2. Major Topics of State and Official Visits

RQ1 aimed to identify major topics of discussion when senior Chinese leaders made diplomatic visits. After the data preprocessing task was completed, the data were converted into data frames for analysis. Consequently, 292,743 words and 8,162 keywords were identified,and the top 50 words are listed in Table 3. A word cloud is a visual representation of text and can be used in various ways. In general, they can be created via pure text summarization. The higher the word frequency in the news, the larger the word size and the closer it is to the cloud center. Conversely, the lower the word frequency, the smaller the word size, and the farther it is from the cloud center. Word clouds aid in understanding the similarity of the presented information to a specific research topic.

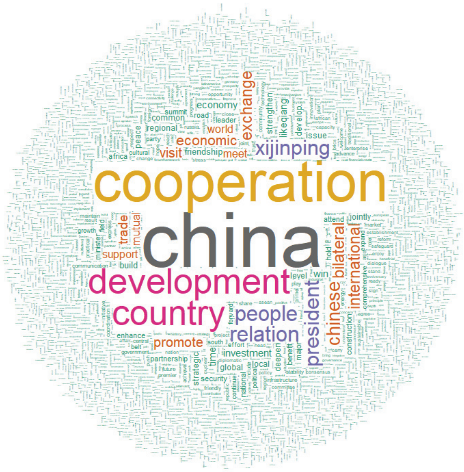
Fig. 4 shows the word cloud obtained for all the countries, which was visualized by extracting the median to maximum values of the word appearance frequency from the entire word quartile. Therefore, it represents more than 130,000 words. The large central words are China, cooperation, development, country, relation, people, bilateral, international, economic, and trade. The word cloud results show the most frequently used keywords in the news. However, word clouds provide a summary of isolated words, and do not suggest their linguistic meanings or relations. Therefore, we conducted a semantic network analysis to determine the meaning of the co-occurring words used in the context.

**Table 3.** Top 50 keywords

| Rank | Word | Frequency | Rank | Word | Frequency |
|---|---|---|---|---|---|
| 1 | china | 10308 | 26 | strengthen | 1115 |
| 2 | cooperation | 7548 | 27 | friendship | 1080 |
| 3 | development | 4762 | 28 | develop | 1062 |
| 4 | country | 4604 | 29 | strategic | 1062 |
| 5 | relation | 2894 | 30 | build | 1050 |
| 6 | people | 2871 | 31 | deepen | 1016 |
| 7 | xijinping | 2776 | 32 | global | 1010 |
| 8 | president | 2755 | 33 | level | 1006 |
| 9 | chinese | 2315 | 34 | common | 997 |
| 10 | bilateral | 2104 | 35 | regional | 962 |
| 11 | international | 2018 | 36 | issue | 958 |
| 12 | exchange | 2004 | 37 | peace | 936 |
| 13 | economic | 1852 | 38 | local | 933 |
| 14 | visit | 1757 | 39 | jointly | 932 |
| 15 | promote | 1689 | 40 | summit | 900 |
| 16 | trade | 1625 | 41 | road | 899 |
| 17 | world | 1486 | 42 | hold | 898 |
| 18 | meet | 1476 | 43 | field | 894 |
| 19 | mutual | 1456 | 44 | leader | 888 |
| 20 | support | 1391 | 45 | enhance | 886 |
| 21 | win | 1261 | 46 | africa | 865 |
| 22 | time | 1245 | 47 | benefit | 862 |
| 23 | likeqiang | 1229 | 48 | minister | 858 |
| 24 | investment | 1209 | 49 | partnership | 849 |
| 25 | economy | 1175 | 50 | security | 848 |

**Note:** A total of 292,743 words and 8,162 keywords were identified.

**Fig. 4.** Word cloud of the keywords



### 4.3. Major Topic Network Structure and Interrelated Research Topics

RQ2 aimed to identify the context of the words related to Chinese senior leaders' diplomatic visits to other countries. Therefore, this study aimed to understand the context of words used during these visits, which can allow us to determine the key topics discussed during the state and official visits. Hence, we performed semantic analysis by tokenizing texts in bigrams. We obtained 41,725 bigrams and 135,434 frequencies, and then produced a bigram matrix.

Table 4 presents the top 30 keywords in terms of degree, betweenness, and closeness centralities. Keywords such as China, Chinese, bilateral, mutual, Xi Jinping, international, economic, regional, cooperation, and trade are interconnected. These keywords are central to the structure and influence other words. In Fig. 5, node size represents the node degree value, which indicates the number of neighboring nodes directly connected to a node. The figure shows 190 nodes and 222 edges. Node degree is one of the key indicators used to measure the importance of a node in the network. Nodes with a large degree are often considered high-connectivity or hub nodes.

The discussion topics were classified according to nine centrality keywords, which are presented in Table 5. Overall, these results indicate that these keywords are important for China in building diplomatic relations with other countries. We also believe that geographically important areas to China are emphasized in the official announcement.

**Table 4.** Top 30 keywords in terms of degree, betweenness, and closeness centrality

| Rank | Word | Degree | Betweenness | Closeness |
|---|---|---|---|---|
| 1 | china | 19 | 171 | 0.0000088 |
| 2 | chinese | 6 | 15 | 0.0000085 |
| 3 | bilateral | 5 | 10 | 0.0000085 |
| 4 | mutual | 5 | 10 | 0.0000085 |
| 5 | xijinping | 5 | 10 | 0.0000085 |
| 6 | international | 5 | 10 | 0.0000085 |
| 7 | economic | 5 | 10 | 0.0000085 |
| 8 | regional | 5 | 10 | 0.0000085 |
| 9 | cooperation | 5 | 10 | 0.0000085 |
| 10 | trade | 5 | 10 | 0.0000085 |
| 11 | strengthen | 4 | 6 | 0.0000084 |
| 12 | south | 4 | 6 | 0.0000084 |
| 13 | global | 4 | 6 | 0.0000084 |
| 14 | national | 4 | 6 | 0.0000084 |
| 15 | win | 3 | 3 | 0.0000084 |
| 16 | road | 3 | 3 | 0.0000084 |
| 17 | common | 3 | 3 | 0.0000084 |
| 18 | development | 3 | 3 | 0.0000084 |
| 19 | world | 3 | 3 | 0.0000084 |
| 20 | deepen | 3 | 3 | 0.0000084 |
| 21 | major | 3 | 3 | 0.0000084 |
| 22 | jointly | 3 | 3 | 0.0000084 |
| 23 | brics | 3 | 3 | 0.0000084 |
| 24 | president | 2 | 1 | 0.0000084 |
| 25 | strategic | 2 | 1 | 0.0000084 |
| 26 | cultural | 2 | 1 | 0.0000084 |
| 27 | time | 2 | 1 | 0.0000084 |
| 28 | infrastructure | 2 | 1 | 0.0000084 |
| 29 | political | 2 | 1 | 0.0000084 |
| 30 | joint | 2 | 1 | 0.0000084 |

**Fig. 5.** Semantic network of high-frequency bigrams


**Table 5.** Discussion topics related to centrality keywords

| Centrality words | Betweenness centrality words |
|---|---|
| China | relation, Africa, EU, CEEC, Russia, sea, south, ASEAN, cooperation, Latin America, Japan, support, development, UK, Germany, country, Vietnam, Pakistan, France |
| Chinese | people, president, enterprise, government, ambassador, premier, delegation, characteristic, economy, business, company, culture, dream, nation, encourage, head, welcome, leader, tourist, market |
| bilateral | relation, cooperation, promote, trade, deepen, practical, tie, comprehensive, economic, push, friendship, diplomatic, exchange, relationship, enhance, elevate, forward strengthen, boost |
| mutual | benefit, trust, political, respect, understand, learn, enhance, support, strategic, deepen, achieve, feature, investment, assistance, equality, bilateral |
| international | community, relation, affair, situation, cooperation, law, organization, financial, economic, production, system, trade, issue, development, environment, import, nuclear, rule, landscape, peace, market, political |

**Table 5.** (Continued)

| Centrality words | Betweenness centrality words |
|---|---|
| economic | development, growth, cooperation, globalization, belt, corridor, recovery, integration, governance, leader, union, situation, investment, partnership, policy, complementarity, structure, zone, social, trade |
| regional | issue, affair, cooperation, peace, economic, organization, country, connectivity, development, security, stability, situation, integration, financial, community, conflict, environment, mechanism, trade |
| cooperation | practical, bilateral, beneficial, strengthen, deepen, capacity, expand, economic, enhance, trade, south, Africa, friendly, international, regional, investment, strategic, BRICS, financial, promote, security |
| trade | free, cooperation, economy, bilateral, investment, system, partner, agreement, multilateral, international, relation, promote, finance, volume, liberalization, global, energy, facilitation, people, friction |

## 4.4. Major Topics Based on Country Classification

RQ3 aimed to identify what is the correlation structure of topic words related to developed and developing countries. The method of co-word analysis was originally applied for target-oriented retrieval and later used to evaluate and present research outputs (Callon, Courtial, & Laville, 1991). Currently, co-word analysis is often used for visualizing information. It allows for a relational analysis of documents based on terms and term groups. This study applied the co-word analysis method to analyze the co-occurrence of networks specified by country classification keywords.

In this study, co-occurrence networks were used to identify topics of discussions in different country groups. Fig. 6 shows the most important words in developed and developing countries. In this network, a node represents a high-frequency word in the official announcement regarding state and official visits, whereas an edge represents the co-occurrence relationship between the two country groups. The words that are centrally located and linked to both developed and developing countries are China, development, cooperation, economics, country, promotion, win, international, exchange, security, culture, economy, politics, growth, cooperation, roads, energy, and regional. The most commonly appearing words when politicians travel around the world are cooperation, security, peace, human rights, cultural exchanges, bilateral relations, and mutual growth are. In particular, words such as roads, energy, and regional represent the importance of BRI, energy, and regionalism-related foreign policy. Words located on both sides are mentioned more frequently in news related to both developed and developing countries. The key topics when Chinese senior leaders visited developed countries were the European Union, Britain, Germany, nuclear security, market, sustainability, reform, and innovation. However, the topics mentioned in developing countries were more diverse. They included BRICS, Latin America, Africa, Asia, Laos, Pakistan, Vietnam, Russia, region, agree, safeguards, stability, communication, future, diplomatic, partner, friendly, comprehensive, coordination, reach, capacity, production, technology, construction, infrastructure, and projects. Consequently, these results show that core topics for promoting foreign policies differ among developing and developed countries.

Additionally, we examined the top TF-IDF for country classification groups to extract words specific to those topics. The table 6 and 7 presents several characteristic words particular to a newsgroup, such as "nuclear security" and "global nuclear," used in developed countries. These words are not important for developing countries. In developing countries, newsgroup topics are "economic investment" and "friendly neighbor." However, these words are less commonly used in developed countries. This result is consistent with that obtained from the co-word analysis. In summary, these results prove that China's diplomatic issues and strategies differ for developed and developing countries.

**Fig. 6.** Co-occurrence network of high-frequency words

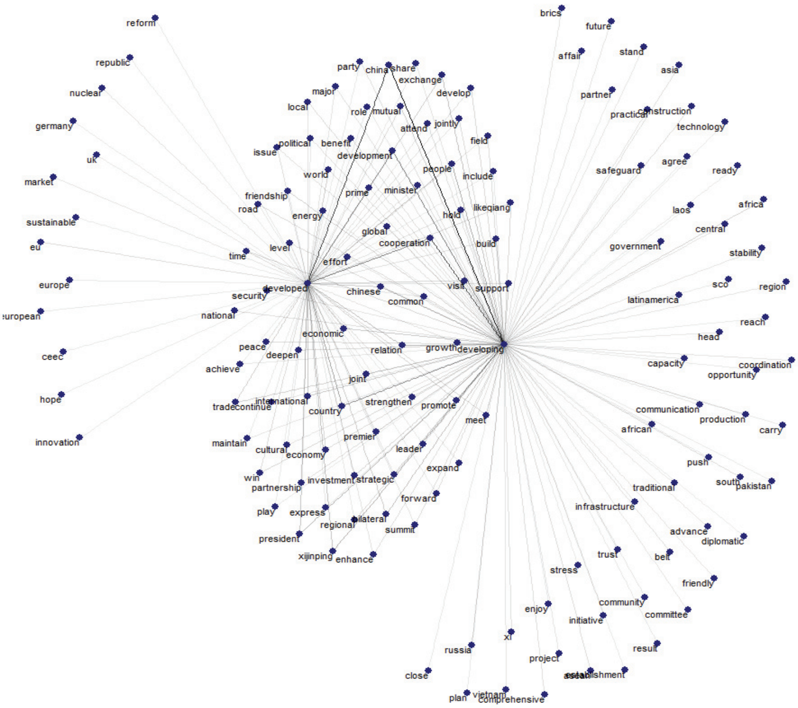



**Table 6.** Top 30 TF-IDF bigram for developing country

| Rank | Bigram | N | TF | IDF | TF-IDF |
|---|---|---|---|---|---|
| 1 | china asean | 160 | 0.002052414 | 0.693147181 | 0.001422625 |
| 2 | china vietnam | 87 | 0.001116000 | 0.693147181 | 0.000773552 |
| 3 | cpv central | 82 | 0.001051862 | 0.693147181 | 0.000729095 |
| 4 | caribbean country | 69 | 0.000885103 | 0.693147181 | 0.000613507 |
| 5 | china laos | 60 | 0.000769655 | 0.693147181 | 0.000533484 |
| 6 | lancang mekong | 51 | 0.000654207 | 0.693147181 | 0.000453462 |
| 7 | china kazakhstan | 48 | 0.000615724 | 0.693147181 | 0.000426787 |
| 8 | china singapore | 47 | 0.000602896 | 0.693147181 | 0.000417896 |

**Table 6.** (Continued)

| Rank | Bigram | N | TF | IDF | TF-IDF |
|---|---|---|---|---|---|
| 9 | johannesburg summit | 42 | 0.000538759 | 0.693147181 | 0.000373439 |
| 10 | lprp central | 40 | 0.000513103 | 0.693147181 | 0.000355656 |
| 11 | arab country | 39 | 0.000500276 | 0.693147181 | 0.000346765 |
| 12 | china belarus | 39 | 0.000500276 | 0.693147181 | 0.000346765 |
| 13 | china cambodia | 37 | 0.000474621 | 0.693147181 | 0.000328982 |
| 14 | patriotic war | 37 | 0.000474621 | 0.693147181 | 0.000328982 |
| 15 | st petersburg | 36 | 0.000461793 | 0.693147181 | 0.000320091 |
| 16 | bandung conference | 35 | 0.000448965 | 0.693147181 | 0.000311199 |
| 17 | economy investment | 35 | 0.000448965 | 0.693147181 | 0.000311199 |
| 18 | island country | 35 | 0.000448965 | 0.693147181 | 0.000311199 |
| 19 | friendly neighbor | 34 | 0.000436138 | 0.693147181 | 0.000302308 |
| 20 | asean relation | 32 | 0.000410483 | 0.693147181 | 0.000284525 |
| 21 | china chile | 32 | 0.000410483 | 0.693147181 | 0.000284525 |
| 22 | asian african | 31 | 0.000397655 | 0.693147181 | 0.000275634 |
| 23 | asean community | 30 | 0.000384828 | 0.693147181 | 0.000266742 |
| 24 | dialogue relation | 30 | 0.000384828 | 0.693147181 | 0.000266742 |
| 25 | economic investment | 30 | 0.000384828 | 0.693147181 | 0.000266742 |
| 26 | asean china | 29 | 0.000372000 | 0.693147181 | 0.000257851 |
| 27 | mekong cooperation | 28 | 0.000359172 | 0.693147181 | 0.000248959 |
| 28 | pacific island | 28 | 0.000359172 | 0.693147181 | 0.000248959 |
| 29 | mekong river | 27 | 0.000346345 | 0.693147181 | 0.000240068 |
| 30 | president nursultannazarbayev | 27 | 0.000346345 | 0.693147181 | 0.000240068 |

**Note:** Developing and developed countries have 25,815 and 22,364 bigrams, respectively.

**Table 7.** Top 30 TF-IDF bigram for developed country

| Rank | Bigram | N | TF | IDF | TF-IDF |
|---|---|---|---|---|---|
| 1 | nuclear security | 214 | 0.003723358 | 0.693147181 | 0.002580835 |
| 2 | china uk | 96 | 0.001670291 | 0.693147181 | 0.001157758 |
| 3 | uk relation | 34 | 0.000591562 | 0.693147181 | 0.000410039 |
| 4 | china finland | 33 | 0.000574163 | 0.693147181 | 0.000397979 |
| 5 | security summit | 33 | 0.000574163 | 0.693147181 | 0.000397979 |
| 6 | china italy | 31 | 0.000539365 | 0.693147181 | 0.000373859 |
| 7 | participant support | 29 | 0.000504567 | 0.693147181 | 0.000349739 |
| 8 | milos zeman | 26 | 0.000452371 | 0.693147181 | 0.000313559 |
| 9 | sergio mattarella | 23 | 0.000400174 | 0.693147181 | 0.000277379 |
| 10 | charles michel | 22 | 0.000382775 | 0.693147181 | 0.000265319 |
| 11 | global nuclear | 22 | 0.000382775 | 0.693147181 | 0.000265319 |
| 12 | nuclear material | 22 | 0.000382775 | 0.693147181 | 0.000265319 |

**Table 7.** (Continued)

| Rank | Bigram | N | TF | IDF | TF-IDF |
|---|---|---|---|---|---|
| 13 | international nuclear | 21 | 0.000365376 | 0.693147181 | 0.000253260 |
| 14 | queen elizabeth | 21 | 0.000365376 | 0.693147181 | 0.000253260 |
| 15 | jean claude | 20 | 0.000347977 | 0.693147181 | 0.000241200 |
| 16 | nuclear terrorism | 20 | 0.000347977 | 0.693147181 | 0.000241200 |
| 17 | president sergio | 20 | 0.000347977 | 0.693147181 | 0.000241200 |
| 18 | beijing china | 19 | 0.000330579 | 0.693147181 | 0.000229140 |
| 19 | bill english | 19 | 0.000330579 | 0.693147181 | 0.000229140 |
| 20 | claude juncker | 19 | 0.000330579 | 0.693147181 | 0.000229140 |
| 21 | china belgium | 18 | 0.000313180 | 0.693147181 | 0.000217080 |
| 22 | elizabeth ii | 17 | 0.000295781 | 0.693147181 | 0.000205020 |
| 23 | piraeus port | 17 | 0.000295781 | 0.693147181 | 0.000205020 |
| 24 | radioactive source | 17 | 0.000295781 | 0.693147181 | 0.000205020 |
| 25 | president emmanuel | 16 | 0.000278382 | 0.693147181 | 0.000192960 |
| 26 | president milos | 16 | 0.000278382 | 0.693147181 | 0.000192960 |
| 27 | albert ii | 15 | 0.000260983 | 0.693147181 | 0.000180900 |
| 28 | eu summit | 15 | 0.000260983 | 0.693147181 | 0.000180900 |
| 29 | prince albert | 15 | 0.000260983 | 0.693147181 | 0.000180900 |
| 30 | eu investment | 14 | 0.000243584 | 0.693147181 | 0.000168840 |

**Note:** Developing and developed countries have 25,815 and 22,364 bigrams, respectively.

## 5. Conclusion

This study used text analysis to identify major topics related to Chinese state and official visits. Text analysis can aid in identifying keywords with high frequencies of appearance and supports the understanding of word pairs that can imply more than one meaning in full sentences. The stored full-news text documents were recalled to the R program to preprocess the text data. We used this program to successfully crawl 1,271 news document records. After the data preprocessing task was completed, the data were converted into data frames for analysis. Consequently, 292,743 words and 8,162 keywords were identified. The main results obtained in this study are as follows. First, the major topics of state and official visits are cooperation, development, country, relation, people, bilateral, international, economic, and trade. Second, state and official visits aim to develop and enhance bilateral ties, and address issues such as politics, human rights, environmental protection, and cultural contacts are common when politicians travel around the world (Lin et al., 2017; Nitsch, 2007). However, economic and diplomatic relations feature most prominently during state and official visits. The discussion topics were classified according to nine centrality keywords are most central to the structure and have the maximum influence in China. Finally, the results showed that China's diplomatic issues and strategies differ between developed and developing countries. The topics mentioned in developing countries were more diverse. The results indicate that core topics for promoting foreign policies differ among developing and developed countries. The bigram TF-IDF results were consistent with those obtained from the co-word analysis.

These results can help researchers studying Chinese economic diplomacy consider keywords related to a particular topic. In particular, roads, energy, and regions represent the importance of BRI, energy, and regionalism-related foreign policy. Therefore, researchers can study combinations of topics such as Chinese economic diplomacy and BRI, Chinese economic diplomacy and energy industry, and Chinese economic diplomacy and regionalism. Scholars studying China and developed countries can investigate China's economic diplomacy with regions such as Asia countries (namely, Australia, Japan, and South Korea) that key security allies with the United States (U.S.) and the European Union (United Kingdom, Germany). Moreover, scholars can explore China's economic diplomacy and the main topics in these countries' markets, know-how, knowledge acquisition, and innovation. In addition, scholars interested in China and other developing countries can focus on China's economic diplomacy and construction, projects, infrastructure trade agreements, production, financial stability, diplomatic relations, and friendly, comprehensive, and strategic diplomatic relations. We hope this study provides a suitable unstructured text and data-based analytical framework for research on economic diplomacy. We propose that text analysis quickly identifies the diversifying direction of economic and diplomatic policies, enabling researchers to conduct empirical studies and select more efficient and appropriate variables to expand their studies.

Understanding economic diplomacy topics can help plan future bilateral/multilateral economic cooperation. And it can help the government and related institutions in decision-making and negotiation. In other words, foreign policymakers, who are perhaps the most important political institutions in other countries, can use the information provided in this study to gain insights into negotiations and establish a good diplomatic relationship with China. Many politicians' international trips announce economic cooperation, such as investment and trade. Moreover, in the official document, the Commission makes important remarks regarding the Chinese strategic approach to the economy, trade, and foreign investment (Fernandes, 2021). Our study takes a step in this direction by proposing a method to help relevant people identify a suitable path toward diplomatic relations by identifying the most important topics and focusing on them during diplomatic visits. That can help reduce friction among countries and put them on a path of homogenous development.

Especially with the increasingly intense China-US strategic competition, there is a sharp debate in the Republic of Korea (ROK) over the strategic choice between the two powers (Chi, 2022). The ROK continues its diplomatic approach of depending on the U.S. for immediate security and China for trade by consolidating the US-ROK alliance to balance China militarily and strengthening economic cooperation with China (Lee, 2017). The reason is that geopolitical considerations certainly play a role among the U.S. key security allies in Asia countries. The purported geostrategic competition between China, on the one hand, and the U.S. and its security allies, on the other hand, need to strengthen the US-ROK alliance and avoid a significant regression in China-ROK relations based on pragmatic diplomacy. So, using the proposed method, the related institute can grasp the direction of China's foreign policy. Moreover, we hope that will help plan the ROK's foreign policy approach and facilitate upgrading China-ROK diplomatic relations. Of course, we also hope it will be equally helpful for other countries in the same condition as ROK.

However, this study had several limitations. First, the conclusions apply only to Chinese diplomatic relations. Therefore, the results must be generalized to other countries. Second, although this study is meaningful in providing researchers with insights into future economic diplomacy, understanding situations and changes in economic and diplomatic relations require expert support in international relations. In particular, text analysis requires contextual knowledge and careful interpretation of international relations. Addressing these limitations can provide a basis for further research.

Future studies could extend the proposed method to analyze the countries' economic and diplomatic relationships. And it will also be meaningful to consider that relationship according to the partnership. In addition, we suggest combining theoretical and unconstructed data-based analytical methods to conduct economic diplomacy research. That could provide important theoretical and methodological insight for research on economic diplomacy.

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