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Analyzing Filipinos' Openness to Trade Partnerships and Globalization Using Sentiment Analysis

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Abstract

Empirical evidence points to globalization to be favorable for the growth and development of a nation. For the Philippines, trade openness and foreign portfolio helped increase per capita GDP as investment and productivity improve. With trade openness and globalization, nations share and gain access to knowledge and technology, inputs of lower costs, new markets, and talents, which improve domestic economic processes. Over the years, however, skepticism about globalization emerged, which affects governments' foreign strategies and policies and, in turn, the realization of intended benefits. With respect to RCEP, which the country signed in 2020, the Philippines is yet to ratify the deal after clamors to delay or reject the deal. Considering the opposing views, this paper aims to analyze Filipino's openness to globalization and trade partnerships using text mining and sentiment analysis to detect evidence that would suggest prevailing perspective towards these issues. In general, the paper finds favorable sentiments towards globalization and trade openness. This study demonstrates the potential of understanding moods and sentiments towards policy to provide distinctive explanatory power that can be used in harmonizing differences in opinions across several domestic and international issues.

Keywords: globalization, international trade, RCEP, sentiment analysis, trade openness

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Francis Mark A. Quimba and Mark Anthony A. Barral

1. Introduction

1.1 Background

The global economy has affected and transformed how nations live and operate. The expanded economic opportunities brought about by globalization led businesses to expand, increasing their profit and giving them more options for brand positioning and investments. Businesses and organizations respond to both domestic and international demands for commodities and services, leveraging shared technology, skills, information, and knowledge. Globalization has boosted economic growth and interdependencies through trade and investment flows, increased productivity, and employment, helped alleviate poverty, and encouraged competition, among others.

Globalization has proven to be beneficial in several ways. Globalization provides access to lower-cost goods and services as more economies gain more comparative advantage from specialization, and diffusion of technologies across borders. For instance, between 1995 and 2006, global exports more than doubled, reaching over US$14 trillion in 2006. Since 1995, global commerce in goods has been expanding at an average yearly rate of 7.5%. It has advanced further since 2000, reaching an average of 13%. Between 2000 and 2006, the average export increase for developing nations was roughly 15.9%, compared to 11.3% and 21.3% for industrialized nations and transitional economies, respectively (UNCTAD 2007). In the case of the Philippines, global integration of the country is evident in the general increase in trade in goods and labor migration. From 1990s to 2000s, the Philippines realized a more open trade, which contributed to its GDP, resulting from its open trade policy in the 1980s. This is also evident in the number of Filipinos migrants, which increased from 3.5 percent in 1995 to 5.4 percent in 2017, in terms of the ratio of migrants to total population (Guinigundo 2018).

On the other hand, however, increasing competition is seen as a threat to domestic products and companies, while new technologies are seen as a threat to traditional jobs. However, due to significant structural obstacles and limitations, a sizable portion of the world is still unable to benefit from globalization. A significant portion of the global population are undereducated and have no means of profiting and benefitting from globalization.

There has been a risk of backlash against globalization, challenging the perception that freer trade provides equal benefits and that it is only good for some but not for others (Erixon 2018).

To further benefit from globalization, and to accelerate the country's recovery from the COVID-19 pandemic, the Department of Trade and Industry (DTI) urged the APEC ministers for inclusive globalization, and to intensify regional and international cooperation to harmonized recovery efforts in trade, investments, and health in the region. DTI also emphasized the need to address uneven recovery across economies by capacitating and empowering vulnerable groups (DTI 2021).

With respect to intensifying the regional and international cooperation, the Regional Comprehensive Economic Partnership (RCEP) is considered a milestone achievement spearheaded by the Association of Southeast Asian Nations (ASEAN) and created to address the “noodle bowl” effect that resulted from the proliferation of free trade agreements (FTAs) in the region, which, instead of helping realize the aims of each trade agreement, only raised the costs of trade (ADB 2022). RCEP was signed by 10 ASEAN countries[1], and Australia, China, Japan, New Zealand, and Rep. of Korea to mark the completion of a decade long negotiation on November 15, 2020. It came into force on January 1, 2022, and is in effect following the ratification by Brunei, Cambodia, Lao, Thailand, Singapore, Vietnam, and Australia, China, Japan, and New Zealand (Kimura et al. 2022).

With over 30% of the world's population, an estimated 30% of the world's GDP in 2019, and approximately 28% of the world's trade, RCEP is considered the largest trading bloc, and large enough to set the agenda for global trade and investment by leveraging infrastructure, technologies, and global value chains (GVCs) (Kimura et al). RCEP is often compared to Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP), which is broader and deeper in scope, while RCEP considers in its goals the development differences of its members (ADB 2022).

The Philippines, however, is still yet to ratify the Agreement, after the ratification has been delayed over clamor from some farmer groups. Concerns from RCEP arise from some belief that the agriculture sector is not prepared to compete in the region due to low productivity, high production costs, poor product quality, among others, as against the competitor’s production, which will make Philippine products less attractive in the regional market (Montemayor 2022). In addition, a rise in protectionism has been documented as a result of globalization and the distributional impacts of international trade prior to COVID-19. Protectionist policies are becoming more popular, which is consistent with earlier protectionism periods based on the idea that globalization benefits the wealthy and powerful at the expense of the middle class (Rodrik 2021, in Kimura et al. 2022).

According to the Department of Agriculture (DA), however, there are already established products that are competitive and ready for the world market, and that RCEP would benefit the country’s agriculture, and that there are placed strategies to meet the demands and atmosphere of trading, including industrialization and modernization of farms to realize economies of scale, improving the value chain to gain competitive advantage, and enhancement of research and development, among others (DA Communications Group 2022).

The National Economic Development Authority (NEDA) and DTI, recently called for the ratification in a joint statement, underscoring the importance of RCEP to boost the economy. NEDA and DTI maintain that the country can reap larger benefits if it joins the Agreement. For instance, RCEP member economies covers roughly 50 percent of Philippine export, 67 of its imports, and 58 percent of its FDI, which is a huge opportunity for the country. The country will also retain 98 percent of its tariff lines, which is about 228 of its commodities. Further, against concerns from the agriculture sector, NEDA-DTI ensure that only 33 of the tariff lines will have lower tariff rates, which is only 1.9 percent of the total tariff lines (0.8% of total agricultural imports) (NEDA 2022).

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[1] ASEAN is comprised of g Brunei Darussalam, Cambodia, Indonesia, the Lao People’s Democratic Republic, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Viet Nam.

In addition, there are earlier claims that, unless RCEP will be able to make significant improvements than the ASEAN+1 FTAs, trade creation within the bloc cannot be expected to be large (Meeryung 2017). There are also concerns that RCEP will be a significantly China-led, increasing China's influence in the region (Rivera and Tullao 2022).

These varying perspectives about the effects of RCEP, and of globalization, trade openness and participation, has become the background for the interest in conducting this study. This paper, therefore, puts forward the following questions:

i. How open are Filipinos to trade partnerships and globalization?
ii. What are the Filipino sentiments in relation to regional cooperation, trade agreements and partnership, globalization, and flows of goods and services?
iii. How do these Filipino sentiments vary across topics and sources?
iv. How can sentiment analysis be used as a trade policy tool?

1.2 Objectives

1.2.1 General Objectives

The study aims to understand the sentiment of Filipinos to trade partnerships and globalization.

1.2.2 Specific Objectives

v. To determine sentiments related to international trade, globalization, and economic and trade cooperation.
vi. To determine how sentiments vary across topics and sources.
vii. To determine the usefulness of sentiment analysis as a decision tool for international policy.

1.3 Scope and Limitations

The paper uses text data from online sources (Twitter and news articles). The tweets and articles retrieved are primarily dependent on the search words used. Twitter text mining is done using a free version of Twitter API, which is subject to some limitations. The sentiments will also depend on the prevailing scenario during which the tweets are posted or the period they are retrieved. For news articles, the procedure is done using Google news text mining. Although this is a common procedure used in analyzing online news articles, the procedure used does not capture the entire article, instead uses descriptions of the articles, which, nevertheless, still contains information on the moods and sentiments conveyed by the articles.

Another limitation is the period of the collection of tweets, which is done between May and October 2022. In addition, and as mentioned earlier, the procedure employed, particularly using free version of the Twitter API, limits the retrieval of only the tweets posted about only six days prior to the time of actual collection. This therefore limits the analysis to capture temporal changes in sentiments. For online news, since there is no similar restriction, earlier articles can still be retrieved. However, for consistency, attempts are not made to conduct temporal analysis using partial data.

Moreover, this paper attempts to describe the overall public sentiment of Filipinos. However, since only a very small portion of tweets contain information about their location, the dataset is limited to tweets that indicate only the language and location (Tagalog or English but within the Philippines), which reduces the size of the dataset.

Lastly, this paper does not attempt to determine how sentiments vary and change within each source of articles and tweets. It is counterintuitive to the purpose and practicality of text and sentiment analysis of determining and understanding the collective and prevailing public moods, perspective, and sentiments; it is understandable that opinion may change over time, and tracking that change at individual level may not be as significant as the changes in collective opinion. It is therefore imperative to focus on the collective sentiments of the public.

2. Overview of RCEP

RCEP is a mega free trade agreement that aims to promote further economic integration among fifteen East Asian and Pacific nations, including ASEAN member economies and Australia, China, Japan, Rep. of Korea, and New Zealand. It is expected to significantly benefit its members as it accounts about 30 percent of the global GDP (ADB 2022 and UNCTAD 2021). RCEP members account about 13 percent of the total global trade in goods or around USD 2.5 trillion, based on 2019 estimates (UNCTAD 2021).

Based on the trends among the RCEP members, in 2019 ASEAN countries make up a larger portion in total imports and exports within RCEP. Of its members, China is undoubtedly the largest player, with about USD 750 billion worth of imports and USD 700 billion in imports with RCEP members, followed by Japan and Korea (Table 1).

Table 1. Trade among RCEP members

	Intra-RCEP Trade (USD billion)		Percentage of Trade with RCEP members	
	Imports	*Exports*	*Imports*	*Exports*
Australia	122	206	56	73
Brunei Darussalam	3	7	52	88
Cambodia	22	9	85	33
China	738	688	39	27
Indonesia	115	101	67	57
Japan	355	321	49	43
Lao People's Democratic Republic	5	6	94	91
Myanmar	16	13	84	67
Malaysia	123	142	60	56
New Zealand	24	26	56	62
Philippines	79	37	68	49
Republic of Korea	233	284	46	50

Singapore	168	222	47	54
Thailand	130	134	61	54
Vietnam	179	117	72	42
RCEP	**2**	**311**	**51**	**45**

Note: figures refer to trade in goods.

Source: Key Statistics and Trends in Trade Policy 2020 (UNCTAD), in UNCTAD (2021, p. 4)

Prior to RCEP, imports trade among RCEP members is largely comprised of electrical machinery and equipment (chapter 85), followed by nuclear reactors, boilers, machinery, and mechanical appliances (chapter 84) (Table 2) (Banga et al. 2021).

Table 2. Composition of RCEP trade in 2019

HS Codes	Description	Percentage share in total trade between RCEP member countries
85	Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles	26
84	Nuclear reactors, boilers, machinery, and mechanical appliances; parts	12
27	Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes	11
26	Ores, slag and ash	4
39	Plastics and articles thereof	4
87	Vehicles other than railway or tramway rolling stock, and parts and acc	4
90	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof	3
72	Iron and steel	3
29	Organic chemicals	2
71	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal, and articles thereof; imitation jewellery	2
73	Articles of iron or steel	2
38	Miscellaneous chemical products	1
40	Rubber and articles thereof	1
74	Copper and articles thereof	1
62	Articles of apparel and clothing accessories, not knitted or crocheted	1
61	Articles of apparel and clothing accessories, knitted or crocheted	1
	Others	22
	Total	100

Source: Banga et al. (2021)

In terms of tariffs, the low MFN rates among RCEP members and the existing bilateral agreements result in generally low average effective applied tariffs on intra-RCEP trade. It can be noted that Australia, Bruenei Darussalam, New Zealand, and Singapore have substantially liberalized all products from other RCEP members. In agricultural products, almost all members have relatively lower rates, except for China, Japan, Rep. of Korea, which have significantly high tariffs (Table 3) (Nicita 2021).

Table 3. Average effectively applied tariffs on intra-RCEP trade

	Overall	Agriculture	Natural Resources	Manufacturing
Australia	0.0	0.0	0.0	0.0
Brunei Darussalam	0.0	0.0	0.0	0.0
Cambodia	3.3	0.6	0.0	4.0
China	2.8	6.7	0.4	3.1
Indonesia	0.9	1.0	0.0	1.0
Japan	1.7	10.2	0.0	1.2
Lao PDR	0.2	0.2	0.0	0.2
Myanmar	0.6	0.2	0.0	0.7
Malaysia	0.9	0.1	0.0	1.1
New Zealand	0.0	0.0	0.0	0.0
Philippines	0.7	0.4	0.0	0.8
ROK	4.8	44.7	0.3	3.1
Singapore	0.0	0.0	0.0	0.0
Thailand	1.7	1.0	0.0	2.0
Vietnam	1.2	1.1	0.1	1.3

Source: Nicita (2021, p. 6)

The Agreement consists of 20 chapters, covering initial provisions, provisions on trade in goods (including rules of origin, customs procedures and trade facilitation, sanitary and phytosanitary measures, and standards, technical regulations, and conformity assessment procedures), services, movement of natural persons, investment, business environment (intellectual property, e-commerce, competition, SMEs, economic and technical cooperation, and government procurement), and general provisions and exception, as well as a provision for dispute settlement (see Annex 1).[2]

RCEP is considered an upgraded version of ASEAN+1 agreements and tries to address new and emerging trade issues, including government procurement, intellectual property, e-commerce, and competition. However, although in the guiding principles followed in RCEP negotiations it was emphasized that RCEP should make significant improvements over the existing ASEAN+1 FTAs (Meeryung 2017), "RCEP follows the 'ASEAN way' of consultation and consensus to manage regional trade integration through a combined agenda of implementation and built-in provisions for making gradual progress in trade liberalization, rather than firm commitments adopted at the outset and contained in the original text" (ADB 2022, p. 1).

[2] This is based on the legal texts of the RCEP Agreement that can be found from https://rcepsec.org/legal-text/.

2.1 Anticipated benefits and costs of RCEP

For the Philippines, RCEP increases the country's access to cheaper consumer goods, as well as raw materials and intermediate goods, which are favorable for manufacturing, as cheaper input costs ensure cheaper production costs. According to DTI (2020), this will make domestic producers more competitive.

RCEP will also provide a better business environment for traders and investors, as provisions on non-tariff measures are enhanced under the agreement. This includes provision and rules on import licensing, clear NTM rules and time-bound consultations, custom procedures, more elaborate SPS and TBT rules, among others.

RCEP offers more room for competitiveness as it provides a more predictable environment, as provided in the chapters on investment, trade in services, intellectual property, e-commerce, and competition, etc. Particularly, investment chapter does not only push for more investment promotion but also covers facilitation and protection of investments, providing more confidence for investors.

In addition, RCEP provides an opportunity to expand market access for services, such as those relating to professional and management services, telecommunications, legal and accounting, architectural, financial, and transport services, among others.

Moreover, RCEP offers a way to complement the country's investment, legal and economic regimes. For instance, the country's developments in MSME can be complemented to RCEP's chapter on SME, especially in terms of integrating in the global value chains (DTI 2020).

In terms of its effects on the domestic industries, RCEP is expected to benefit the construction, transportation, and machinery equipment, due to higher inflows of foreign investments. RCEP, however, goes without some costs. The entry of cheaper rice, although seen to be favorable to consumers, is seen to negatively affect domestic rice producers. Similarly, the entry of cheaper textiles may also affect domestic textile industry but is seen to favor the garments and apparel industry (Cororaton 2016).

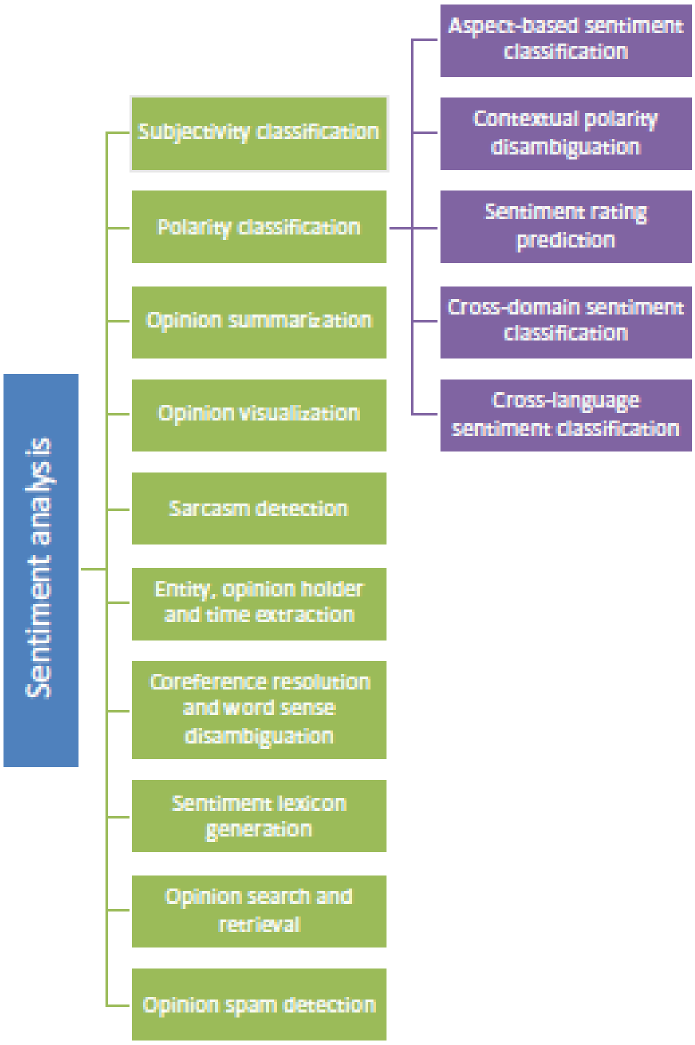
For Philippine trade, the anticipated effects in exports and imports to participating countries vary. Positive net effects for exports are observed in 8 out of 14 participating countries, with South Korea showing to be the highest source of opportunity for the country, followed by Malaysia and Myanmar, while the country does not seem to benefit from export trade with China, Thailand, and Japan (Annex 2). Consequently, these translate to overall positive net effects in the country's output, employment, and household income (Annex 3) (DTI 2020).

3. Overview of Sentiment Analysis

Sentiment analysis is the process of understanding the emotional intent inferred from each media source, and classifies words and expressions based on polarity, whether positive, negative or neutral (Silge and Robinson 2017, and Nafees et al. 2019), or categorizes emotions, such as "happy", "sad", "afraid", or bored" (Bisio et al. 2017, and Nissim and Patti 2017), or emotion mining. "The aim of sentiment analysis is therefore to define automatic tools able to extract subjective information in order to create structured and actionable knowledge" (Pozzi et al. 2017, p. 2). It is a quality metric that looks behind numbers to understand how opinions, attitudes, and emotions are conveyed by the user (Pallavicini et al. 2017).

Sentiment analysis can be used to understand the needs of organizations and customers; identify, monitor, and remove spams; identify clusters of words; measure and evaluate impacts; and simplify, analyze, and visualize data; among others (Bhargava and Rao 2018). It is also called opinion mining or extraction, subjectivity analysis, affect analysis, emotion analysis, or review mining, among others, depending on the use and field of application (Pozzi et al. 2017). Figure 1 presents tasks involved in sentiment analysis.

Figure 1. Sentiment analysis Tasks



Source: Pozzi et al. (2017)

Analyzing sentiments can be done at three main levels – sentence, concept, or document (Nafees et al. 2019). The sentiment of a text is most commonly analyzed by treating the text as a combination of individual words, and the total sentiment content of each word as the sentiment content of the whole text (i.e., sentiment analysis by word). Some algorithms, however, go beyond the individual words and capture sentiments based on the combination of words (i.e., sentiment analysis by message) (Silge and Robinson 2017). Concept- and context-based analysis leads to better understanding of expressed texts and reduces the gap between unstructured and structured information. Concept-level sentiment analysis goes beyond the use of keywords, word frequencies, and co-occurrence counts, and can better recognize implicit meaning (Nissim and Patti 2017).

The use of text as data has been gaining popularity in the fields of sciences, including economics and international trade. Like text mining and other natural language methodologies, sentiment analysis can be used to extract unstructured information from and analyze the structure of texts to detect market and trade indicators.

The use of text analysis has been extensively explored, especially in policy analysis. Text-as-data has been used to detect events and monitor conflicts or the possibility of such occurring. From key word matching to encode events of attacks to syntax parsing, lexical databasing, to classification of political texts using machine learning techniques have been well documented (Gilardi and Wuest 2018).

In the field of environmental science, Wei et al. (2021) explored the use of sentiment analysis to understand the values and interests of riparian countries, which affect their propensity to engage in cooperative water management and treaties or agreements. By analyzing news articles, the trends of water conflicts and the cooperation initiatives that arise are defined, suggesting differences in the sentiment and inclination to cooperative management across countries.

Shapiro et al. (2020) analyze economic sentiments from economic and financial news articles and demonstrate how positive sentiments can positively stimulate macroeconomic variables (i.e., increase consumption, output, and interest rates, and reduce inflation). Similarly, Fraiberger (2016) tracks the fluctuations in GDP growth by constructing a sentiment index that measures the positive expressions in Reuters news articles and finds that sentiments can be a leading indicator of GDP.

Despite these studies, text-as-data analysis is not yet considered a conventional technique in comparative policy analysis. Still, there have been many applications existing. For instance, it is used to develop a measurement system to classify political activities into topics that can be compared through time and across domains or systems (Baumgartner and Jones 2018, in Gilardi and Wuest 2018). Text analysis is also used to define problems to understand what the problems are and, more importantly, how to address them (problem definition); understand how policies interact or how policies in an area affect the policies in another (policy diffusion); identify the frames used by interest groups (lobbying); and in gathering feedbacks to understand the effects of policies (policy effects) (Gilardi and Wuest 2018).

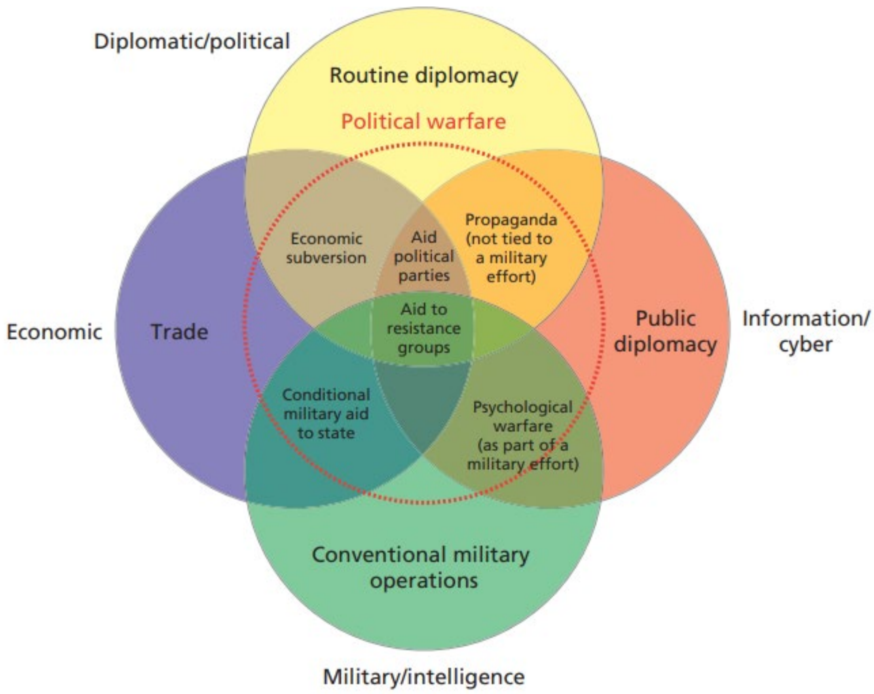
In the analysis of international trade, texts of trade agreements can be analyzed to determine their impacts on trade. The texts of trade agreements (ToTA) are machine readable and can be used to build text-as-data indicators of trade (Seiermann 2018). Meaningful variations between texts or chapters of or of the whole agreements can be determined using text similarity, which can be incorporated in a gravity model to estimate and predict trade flow impacts of an agreement (Alschner et al. 2017; Quimba and Barral [forthcoming]). Analyzing the texts of agreements can also be used to determine how a country's influence dominates an agreement by measuring the share of the text that is identical to previous agreements entered by that country (Seiermann 2018).

Haren (2017) evaluates the extent to which international trade flows predict sentiments across countries, and vice versa. The analysis considers dyadic interactions involving trade flows between 40 countries and the sentiments towards each other. The data included in the analysis are dyadic interaction, which is formed by two countries having a directed relationship, region, sentiment, and values of export and import. The data is divided into training set (75%) and test set (25%). Four regression models are employed in the study – baseline, ridge, random forest, and support vector regression (SVR). The results reveal that the regression models on unseen data perform better than those in the training phase and suggest that the baseline model is outperformed by other regression models, with the SVR yielding best results. The study finds that trade flows can in fact predict sentiments two years ahead and that sentiments can be more predictive in future imports than exports.

In international relations, understanding foreign policies can be crucial in deciding the position of a country on a certain issue. Information derived from different sources, including texts, is one of most important instruments of national power. The others are diplomacy, military, and economic). Information refers to how countries transmit their image and position to influence the rest of the world, and so monitoring this information is crucial for national security and foreign policy (Fisher, Klein, and Codjo 2022).

Governments typically rely on information to understand sentiments, shape public opinion, or create favorable conditions in order to accomplish national interest, achieve strategic global positioning, and protect national security (Figure 2). The use of information, or in combination with other implements of power, characterizes the modern political warfare, which highlights the importance of utilizing information and communications technology, and therefore enhancing capabilities of drawing hidden information across a variety of sources (Robinson et al. 2019).

Figure 2. Sentiment analysis Tasks



Source: Robinson et al. (2019)

Thus, Sentiment analysis is a useful tool in the analysis of information as an instrument of national power. Sentiment analysis helps transform language into quantitative facts by measuring opinion on a subject drawn from innumerable sources. Analyzing governments' official narratives helps better understand their implications, how they respond to crises, their foreign policies, and their interests to favorable and unfavorable events (Fisher et al. 2022).

In recent years, social media platforms have become an important tool for political communication, propaganda, and mobilization, which sometimes even surpass mainstream channels. Politicians and policy makers do not only appear online but have become increasingly interested in monitoring and responding to online perceptions and attitudes (Hatipoglu et al. 2019). For instance, in the Philippines social media, as the new media, helps the flow of political and social information, which may potentially be dominated by political and social elites, although the diversity and number of users, with diverse backgrounds and beliefs, may somehow remedy this unlikely scenario. The number game plays an important role in how conversations about politics and social issues spread and are highlighted in different networks and platforms (Pertierra 2012). With sufficient resources, social media sites shape networking platforms into a dynamic electoral machinery, integrating the political consciousness of the people, considering as well that a relatively large portion of the Filipinos have access to internet and technology (Espina-Letargo 2010). Social media significantly shapes the evolution of Philippine democracy, and, when appropriately used, can enhance political discussion within the community, increasing the citizens' level of awareness (Griffith Asia Institute 2020).

With the help of computer coding techniques, policy positions of parties or entities can be drawn from political texts, by reducing a large and complex text from social media and other publications in to a smaller and simpler set of data and then processing them into variables that can be used to model this policy information (Laver and Garry 2000).

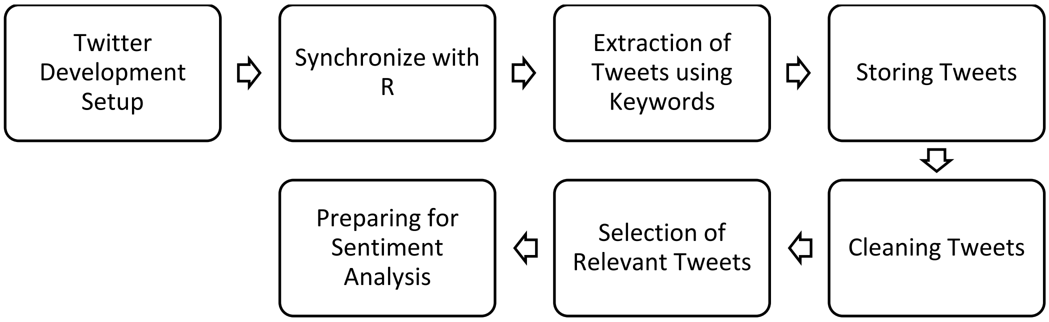
4. Methodology

4.1 Text Mining Tweets and News Articles

The text data used in this paper are gathered from two main sources, tweets, and news, which are gathered using different methods.

In Twitter mining, there are several requirements needed for one to be able to download tweets. First is to set up a Twitter account and create an app. This is important when connecting Twitter to other apps or programs such as R. Using the app, one will be able to generate important information or identification elements: *appnam*, key, and secret. These are authentication keys (also called consumer key and consumer secret) that are passed to Twitter API and provide access to the Twitter environment to be able to make queries, such as sending, searching, or retweeting tweets (Wasser 2017). Figure 3 presents the process of collecting and preparing tweets for analysis.

Figure 3. Tweet extraction workflow



Source: Authors' construct

The R package used in this paper is *rtweet*, which is becoming a standard tool to access Twitter data. [3] For mining texts using Google news, *rvest* package is used.

Below is a sample code in accessing Twitter app using R studio:

Box 1: Sample code in access Twitter API

```
# Authonitical keys
twitter_token <- create_token(
        app = "xxxxxxxxxx",
        consumer_key = "upwxxxxxxxxxx",
        consumer_secret = "vfZxxxxxxxxxxx ",
        access_token = "143xxxxxxxxxx ",
        access_secret = "Nj2xxxxxxxxxx ",
        set_renv = TRUE)
```

Source: Authors' construct

Unlike Twitter, mining texts using Google news is quite simpler and straightforward, which requires only the links containing the keywords of interests. For example, the following line contains the URL that identifies news articles relating to "Philippines" and "RCEP":

```
source_web="https://news.google.com/search?q=Philippines%20RCEPhl=en-PH&gl=
        PH&ceid=PH%3Aen"
```

Here, the "source_web" is the name assigned to the data frame to contain the url object or the web address representing the Google News feed for the articles that mention "Philippines" and "RCEP", as sample search words. The URL is simply copied from the browser and pasted into

[3] For the step-by-step process, this link discusses how Twitter authentication is done using *rtweet: https://cran.r-project.org/web/packages/rtweet/vignettes/auth.html.*

the R script, which is used to make a request to the server and allow R session to read the HTML and download the texts on the page.[4]

Some of the basic elements of tweet structure retrieved and can be used in tweet analysis include the following:

- handle – unique username that begins with "@"
- time stamp – shows the time the tweet was posted
- text – the main body of tweet
- hashtag – a unique identifier of a particular event or topic that begins with "#"
- links – hyperlinks embedded within a tweet to share information
- embedded media – graphic elements
- replies – tweets posted in reply to a particular tweet
- retweets – shared or forwarded tweets
- latitude/longitude – location identifier[5]

Retrieving news text using Google news, on the other hand, the R script returns the following information:

- title – headline of the article
- link – source of the article
- description – 1- or 2-liner summary of the article
- source – name of the content creator
- time – date of publication

In extracting tweets and news texts using keywords, the following guidelines are used.

Table 4. Guide in extracting text data using keywords

Requirements	Keyword
Must include the following words:	Philippines
Includes at least one of the following related words:	Trade/economic/regional cooperation/partnership, trade, trade in goods, trade in services, international trade, globalization, investment, sustainability, West Philippine Sea, South China Sea, pandemic, Covid, migration, …
Includes at least one of the following words related to countries and blocs involved:	USA, China, Japan, Australia, RCEP, …

Source: Authors' construct

[4] The URL is the search result URL. This varies depending on the search words (and the search settings) used in searching for articles. The format of the script may vary on the package or tools used.
[5] Only about 1% of all tweets contains coordinate information.

4.2 Determining the Sentiments of Texts

There are various techniques to model a text written in natural language from a mathematical perspective. Texts are often coded in the context of text mining as a collection of words or *bag of words*, which can be thought of as an unorganized collection of words and has no syntactic and grammatical categories. Text parsing makes it possible to distinguish between the various tokens present in the collection and to compile a list of different token types, or vocabulary. (Misuraca et al. 2020).

Consider a collection of n texts d_i (i = 1, …, n). Each d_i is represented as a vector space containing p terms belonging to the vocabulary:

$$d_i = \{t_{i1}, \ldots, t_{im}, \ldots, t_{ip}\} \tag{1}$$

where t_{im} represents the importance of the m-th term in d_i. The importance is often measured by the *term frequency*, or the number of occurrences of a term in a document (other weighting schemes can also be considered). The document-vectors can be arranged in a matrix X form having n rows (documents) and p columns (terms) (Misuraca et al. 2020).

The goal of sentiment analysis is to classify terms according to their polarity (positivity or negativity, or subjectiveness or objectiveness) by identifying their semantic orientation. The overall polarity of texts reveals the semantic orientation of the document. The different levels of semantic orientation are as follows (Misuraca et al. 2020, p. 3):

a) the subjectivity/objectivity of a document (SO-orientation): the focus concerns if a text has a factual nature or instead expresses an opinion on its subjective matter;
b) the positivity/negativity of a document (PN-orientation): the focus concerns if a subjective text expresses a positive or negative opinion;
c) 3. the positivity/negativity strength of a document (PN-strength): the focus concerns the identification of different grades of positive or negative sentiments in the text.

Sentiment analysis can be done at either of the levels of analysis, document-level, sentence-level, or aspect-level. The document-level defines the orientation of the overall text, whether positive or negative. In the sentiment-level, documents are broken down into sentences and the polarity of each sentence is calculated. The overall polarity is then used to synthesize the orientation of the document. Aspect-level is a topic-based approach (Misuraca et al. 2020).

In evaluating the PN-orientation of documents, polarity scores are calculated, which can be represented by -1 (negative), 0 (neutral), and +1 (positive). The polarity scores depend on lexicon or a list of polarized terms, which may be created manually, automatically, or semi-automatically (Misuraca et al. 2020).

Among the standard lexicons commonly used are *syuzhet*, afinn, *bing*, and *nrc.* The *syuzhet* vector has a corresponding sentiment value ranging between -1 and 1 (decimal, 16 values or resolution), the *bing* vector assigns binary scale of -1 and +1 (2-range resolution), while the *afinn* vector assigns values between -5 to +5 (integer, 11-range resolution) to determine the strength of positivity or negativity of tweets. Emotion classification can then be done using the NRC lexicon to associate the tweets to “anger”, “anticipation”, “disgust”, “fear”, “joy”, "sadness", "surprise" (Naldi 2019). Table 5 summarizes how these lexicons calculate or score words for classification.

Table 5. Calculation and scoring method of sentiment lexicons

Lexicon	Calculation Method to Obtain Score
syuzhet	Scores individual words and sum
afinn	Scores individual words and sum
bing	(Number of positive words - number of negative words)/total words
Nrc	(Number of positive words - number of negative words)/total words

Source: Based on Sonkin (2021)

The *syuzhet* lexicon is developed by the Nebraska Literary Lab, under the direction of Matthew L. Jockers, as a data frame of two columns containing 10, 748 terms. About 66 percent of the terms in this lexicon are negative. The *afinn* is developed by Finn Arup Nielen as the AFINN Word Database, which contains slang and obscene words commonly used on the Internet, and extended to contain used words in Twitter, as well as from the Urban Dictionary and Wiktionary to include acronyms and abbreviations. It contains a much lesser number of 2, 477 words, with about 65 percent negative. The *bing*, on the other hand, is developed by Minqing Hu and Bing Liu as Opinion Lexicon, containing 6, 789 words having a larger portion of 70 percent negative words (Table 6) (Naldi 2019). As these lexicons contain different number of positive and negative terms, they also have different advantages and disadvantages in capturing and scoring the polarity of documents.

Table 6. Number of words per lexicon

Lexicon	No. of Words	No. of Positive Words	No. of Negative Words	Resolution
syuzhet	10748	3587	7161	16
afinn	2477	878	1598	11
bing	6789	2006	4783	2

Source: Naldi (2019)

Distinct to the three lexicons, the *nrc* scores and categorizes terms not just purely in terms of polarity. Instead, it uses additional categories of sentiments or emotions – anger, anticipation, disgust, fear, joy, sadness, surprise, trust, in addition to positive or negative. It contains a total of 13, 889 words that are distributed across these categories (Table 7) (Naldi 2019).[6] The *nrc* is developed by Saif M. Mohammad and Peter D. Turney, as the NRC Emotion Lexicon (Widyaningrum et al 2019).

[6] Some words may be in more than one category, so the total is different.

Table 7. Number of words in *nrc* lexicon

Category	No. of Words
Anger	1247
Anticipation	839
Disgust	1058
Fear	1476
Joy	689
Sadness	1191
Surprise	534
Trust	1231
Positive	2312
Negative	3324

Source: Naldi (2019)

To illustrate how the lexicons score a text, take for example the sentence "This device is perfect but noisy". Using the *afinn* lexicon, the words "perfect" and "noisy" will be detected and scored +3 and -1, respectively. The overall sentiment score for that is therefore the difference of 2. In *bing*, the overall sentiment will be 0 as, again, it gives score of only either +1 and -1, respectively. With *nrc*, whenever a text contains a word belonging to each of its categories (i.e., disgust), that word leads to one count in the sentiment score for that category. In other words, if a sentence contains 3 words that can be found in the category disgust, the sentiment score of that sentence in the disgust category will be 3 (Naldi 2019).

These four lexicons are available in the *syuzhet* package in R. There are several other lexicons and packages available in the literature, each of which have advantages and disadvantages, especially with respect to accuracy and speed. For practicality, this paper utilizes these lexicons and the *syuzhet* package.

Before formally categorizing the terms and documents into different polarities, it is important to do a pre-processing to decrease the vocabulary's dimensionality and discard non-informative categories. Figure 4 presents the workflow followed to undertake the sentiment analysis in this paper.

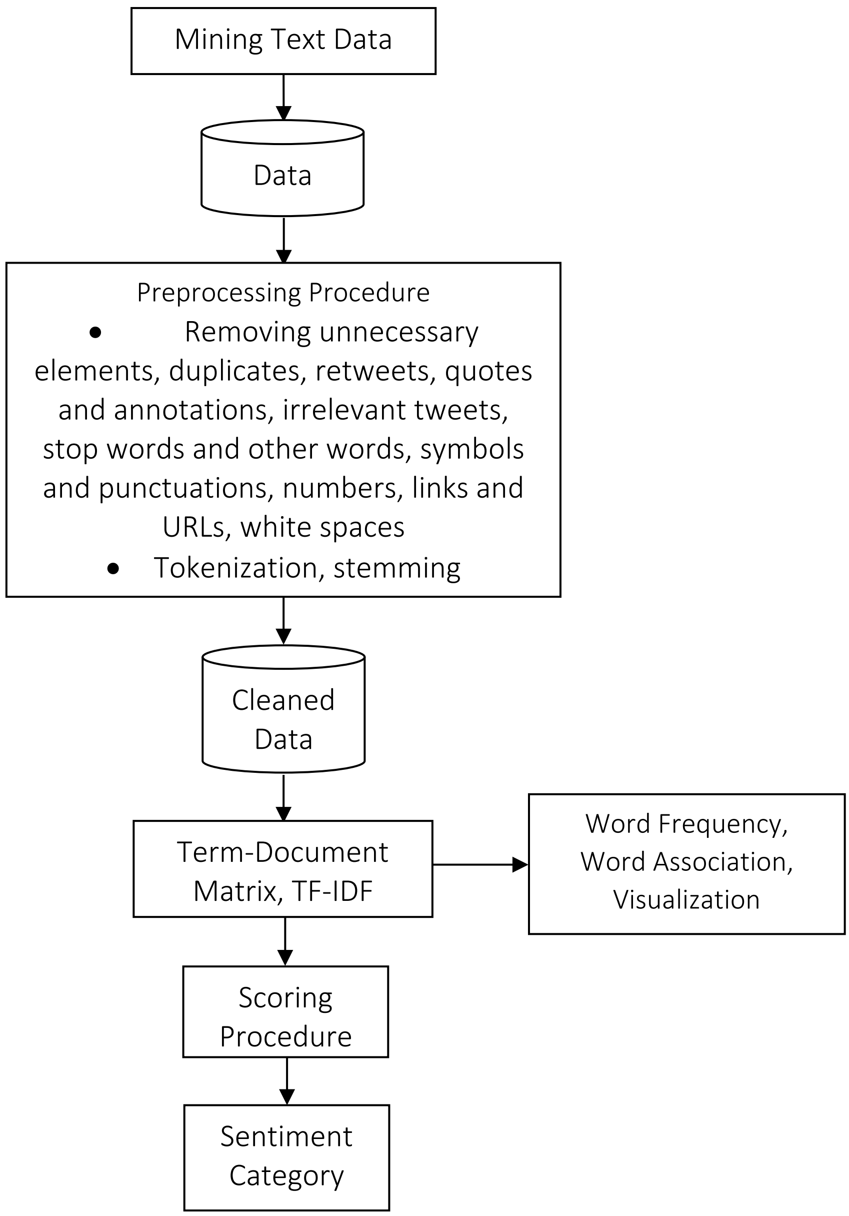
Preprocessing is a usual procedure conducted in text analysis. This is done to eliminate unnecessary and irrelevant information that may lead to misleading results. Symbols, numbers, spaces, and non-standard and non-English words are also eliminated. For other languages, especially those of interest, such as Tagalog, translation to English may also be conducted. This can be done using a number of available procedures, such as using Google Translate. In large datasets, translation may not be perfectly accurate but in some cases remains helpful to avoid missing important and relevant information.

The importance of terms in texts is typically based on their relative frequency. Thus, building the term document matric gives insights on what are the more important terms used in each document. Using the Term Frequency Inverse Document Frequency (TF-IDF), the weight of a count of term against a positive or negative sentiment is normalized. This is done using the following formula (Widyaningrum et al. 2019):

$$tfidf(word) = tf(word)xlog\frac{N}{df(word)} \tag{2}$$

In addition, word association and visualization are also done to illustrate some insights.

Figure 4. Workflow of sentiment analysis

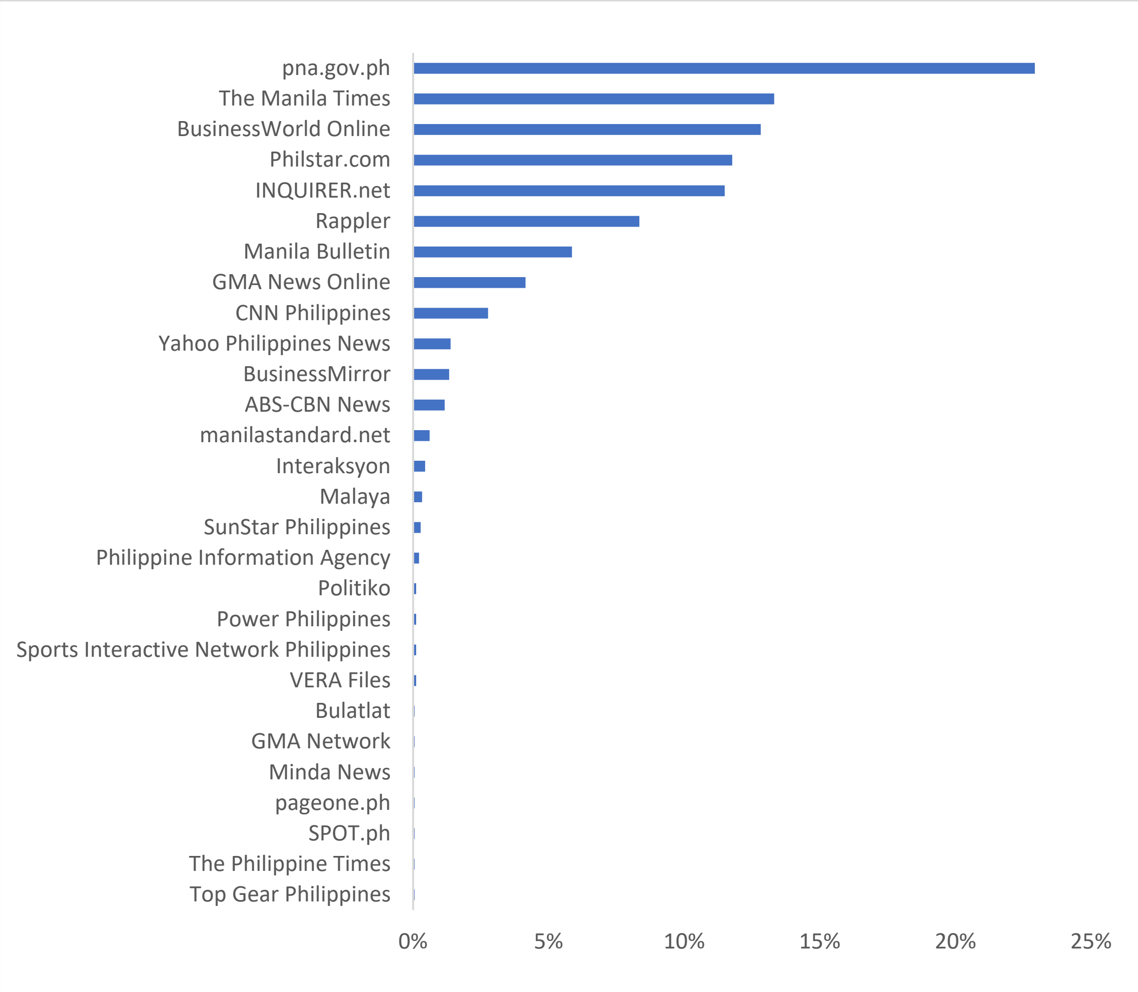


Source: Authors' construct

4.3 Data Collected

From May to October 2022, more than 300, 000 tweets and more than 7, 100 online news were collected. After pre-processing and carefully considering the limitations (i.e., noise contained in tweets, irrelevant information), a total of 7,554 tweets and 1,794 news are processed for the analysis. News texts considered in the study are only those that are published by local sources. Figure 5 presents the distribution by sources.

Figure 5. Distribution of news by source



Source: Authors' construct

5. Results and Discussions

5.1 Word Frequency and Themes

Table 8 presents the most used words from the texts gathered from both tweets and online news that refer to selected partner countries and neighbors of the Philippines. Individual words do not seem to provide any information, as a collection, however, they seem to reveal some insights and themes about public perception and interests towards these countries. For instance, for Australia, terms like "president", "trip", "travel" may entail the reported visit of the newly elected Philippine president right after the election, which is within the period the tweets and online news are gathered in the study. Similarly, the term “secret” may refer to the reported secret letter of Queen Elizabeth to Sydney, which sparked interests around the world, including the Filipinos.

Table 8. Top 10 most frequent words, by country

Australia	Canada	China	Indonesia	Japan	Korea	Malaysia	Thailand	USA	Vietnam
presid	olympic	sea	game	abe	run	women	women	export	seagame
secret	filipino	south	seagame	minist	man	fever	team	import	game
avccup	good	presid	gold	prime	show	game	game	econom	malaysia
ambassador	join	west	team	shinzo	runningmanph	seagame	final	global	medal
trip	unite	relat	women	visit	game	gold	volleybal	rcep	gold
fun	life	live	medal	fiba	adapt	gila	seagam	invest	women
dutert	work	joint	volleybal	presid	visit	basketbal	men	foreign	team
game	race	dutert	win	world	seoul	team	first	tie	sea
season	support	oil	final	offici	star	sabah	medal	boost	asian
travel	trade	made	basketbal	friend	travel	win	footbal	dti	final

Source: Authors’ calculation

For Indonesia, Malaysia, Thailand, and Vietnam, it is interesting to note that the most frequent words reveal almost similar theme pertaining to sports and the SEA Games, which was held sometime in May 12-23, 2022, in Vietnam.

Top words for China and USA seem to provide hints about some geopolitical topics. For Japan, while the terms reveal a combination of themes, more predominant terms refer to the recent demise of the former prime minister Shinzo Abe.

Filipinos interest and fanaticism to the Korean culture seem evident in the terms “run”, “man”, “show”, “runningman”, and “adapt”, which may refer to the Philippine adaptation of the popular Korean TV series, Running Man, which has been making trends for several weeks.

For Canada, on the other hand, the most frequent terms do not seem to reveal a common theme.

Similarly, Table 9 presents the topmost commonly used words in the gathered tweets and news pertaining to RCEP and trade openness. For RCEP, apart from the expected terms such as “trade”, “econom(y)”, “region”, “partnership”, and “comprehens(ive)”, the terms also seem to reveal an issue about the Philippines’ “ratifi(cation)” of the agreement. On the other hand, for trade openness, common and expected terms also make the topmost frequently used terms.

Table 9. Top 10 most frequent words, RCEP and trade openness

RCEP	Trade Openness
trade	trade
econom	export
region	import
partnership	econom
senat	global
comprehens	rcep

ratifi	invest
agreement	foreign
join	rice
deal	deal

Note: RCEP - Regional Comprehensive Economic Partnership

Source: Authors' calculation

5.2 Overall Sentiments

The results of classification and scoring reveal that the sentiments, in general, are positive. It is interesting and should be noted that these sentiments do not necessarily reflect the moods of the issues and themes revealed based on the term frequency. For instance, with Japan, despite information about the demise of its former prime minister, the sentiments of the texts across sources are generally positive. For China and Canada, *affin* and *bing* lexicons score the texts gathered from online news as negative. For both tweets and news, *bing* indicates negative sentiment for China.

For RCEP and trade openness, on the other hand, overall sentiments appear to be positive (Table 10).

Table 10. Overall sentiment scores, by source and topic

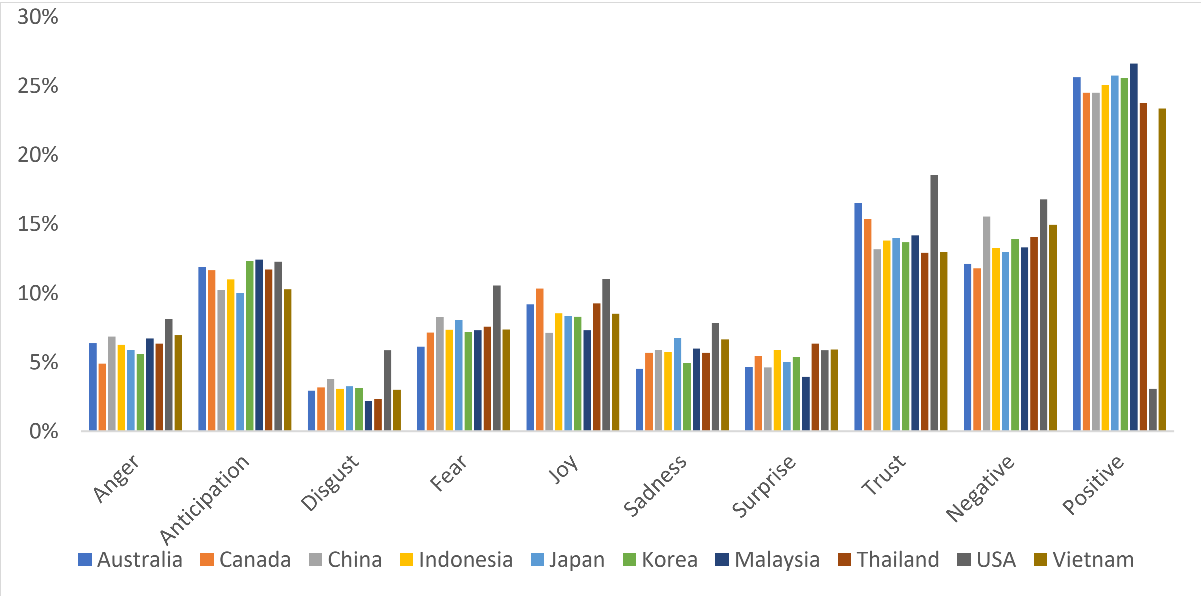
Topics	Tweets			Online News			Tweets and News		
	Affin	Bing	Syuzhet	Affin	Bing	Syuzhet	Affin	Bing	Syuzhet
Australia	161	50	78.0	9	6	7.2	157	50	76.3
Canada	114	23	62.5	-11	-1	11.3	122	36	75.1
China	26	2	26.9	-5	-6	0.4	14	-2	23.6
Indonesia	129	41	81.5	6	5	7.9	127	43	84.0
Japan	173	35	106.5	25	17	16.2	174	37	109.2
Korea	86	30	39.6	-7	4	12.6	66	30	46.7
Malaysia	92	26	55.4	1	-1	1.0	85	21	52.4
Thailand	137	43	63.9	24	11	11.5	138	42	67.9
USA	173	16	132.2	11	8	16.2	165	16	130.3
Vietnam	89	31	53.7	14	6	8.9	77	20	51.6
RCEP	47	13	27.2	21	13	17.5	51	17	33.2
Trade Openness	70	14	38.3	79	39	72.7	133	43	97.1

Note: RCEP - Regional Comprehensive Economic Partnership

Source: Authors' calculation

For *nrc*, the results reveal an overall positive sentiment across countries for the collected tweets, except for USA. Across emotion categories, the *nrc* lexicon detected a relatively higher level of trust, followed by anticipation, joy and fear. The USA surprisingly appeared to gain the highest trust despite having a very low positive sentiment (Figure 6).

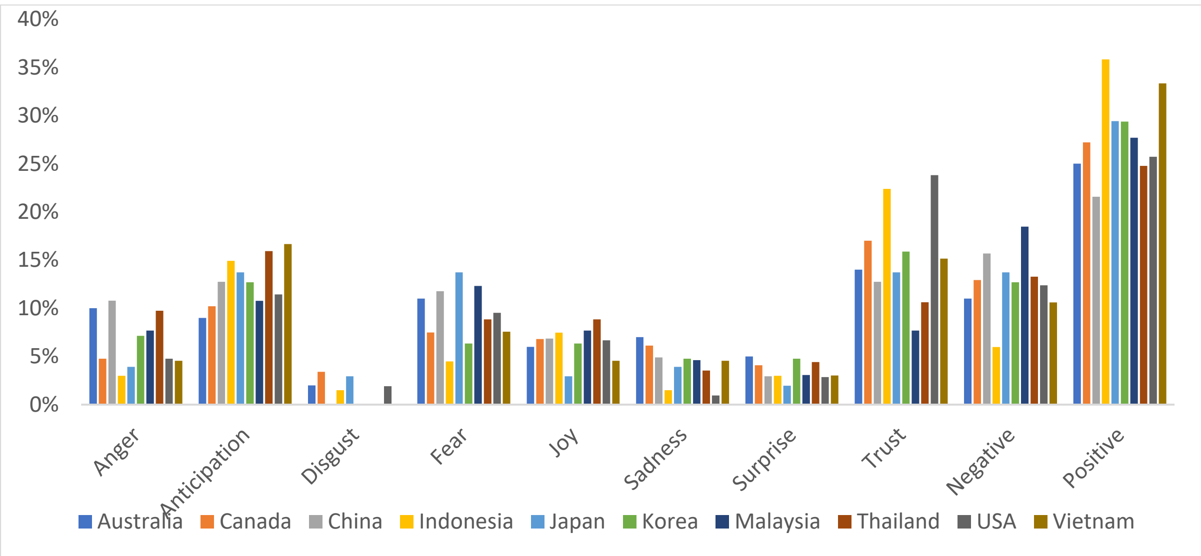
Figure 6. *nrc* results for selected countries, tweets



Source: Authors' calculation

In terms of online news, the situation appears to be different, where all countries appear to have generally positive sentiments. In emotion categories, trust also appears to be most prevalent in news, followed by anticipation and fear. The USA also appears to have highest trust scores, followed by Indonesia and Canada, while Malaysia and Thailand are least trusted, followed by China (Figure 7).

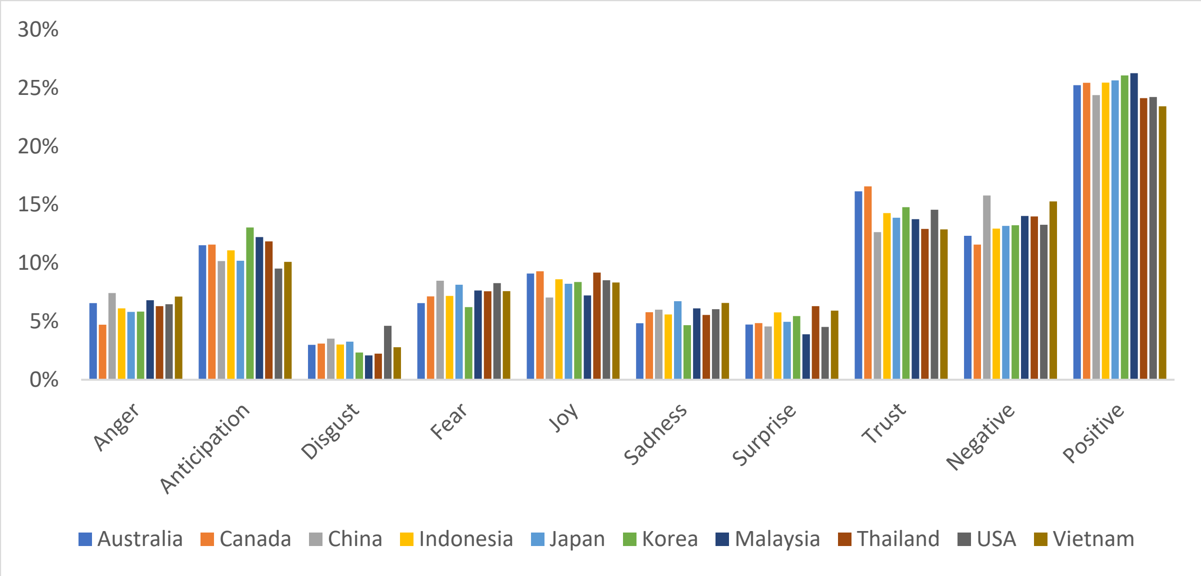
Figure 7. nrc results for selected countries, online news



Source: Authors' calculation

Overall sentiments across all sources indicate higher levels of positive scores. Trust remains to be highest, followed by anticipation. Most positive sentiments are associated with Malaysia and Korea, while most negative sentiments China, which also appears to gain the least trust (Figure 8).

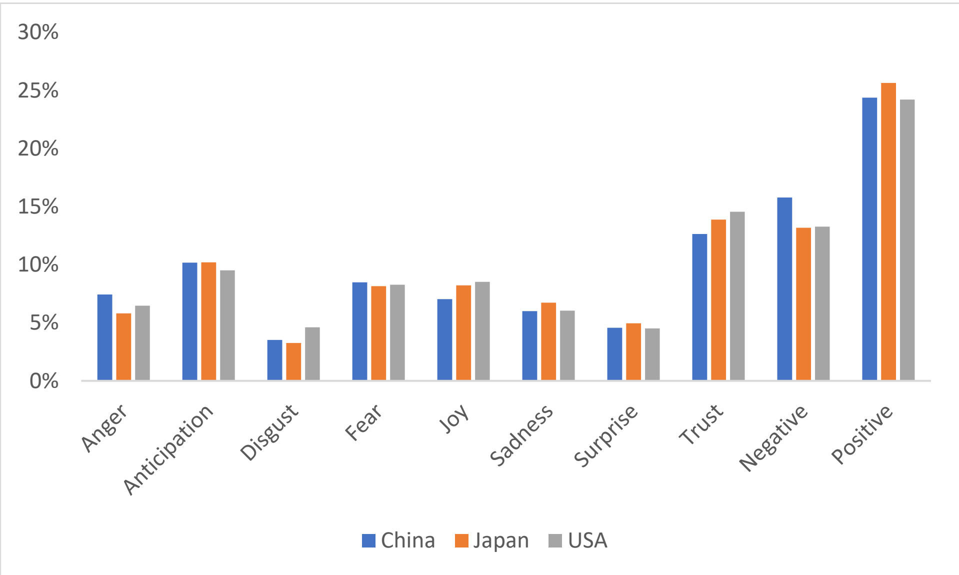
Figure 8. nrc results for selected countries, tweets and online news



Source: Authors' calculation

Figure 9 highlights the sentiments of the three largest global economies. Of the three, Japan appears to be a source of more positive sentiments, while there seems to be no distinction between China and USA. In terms of negative sentiments, however, China tops the list, while there is no distinction between the other two. In terms of emotions, trust is highest with USA, followed by Japan and China.

Figure 9. *nrc* results for top 3 largest economies, tweets and online news

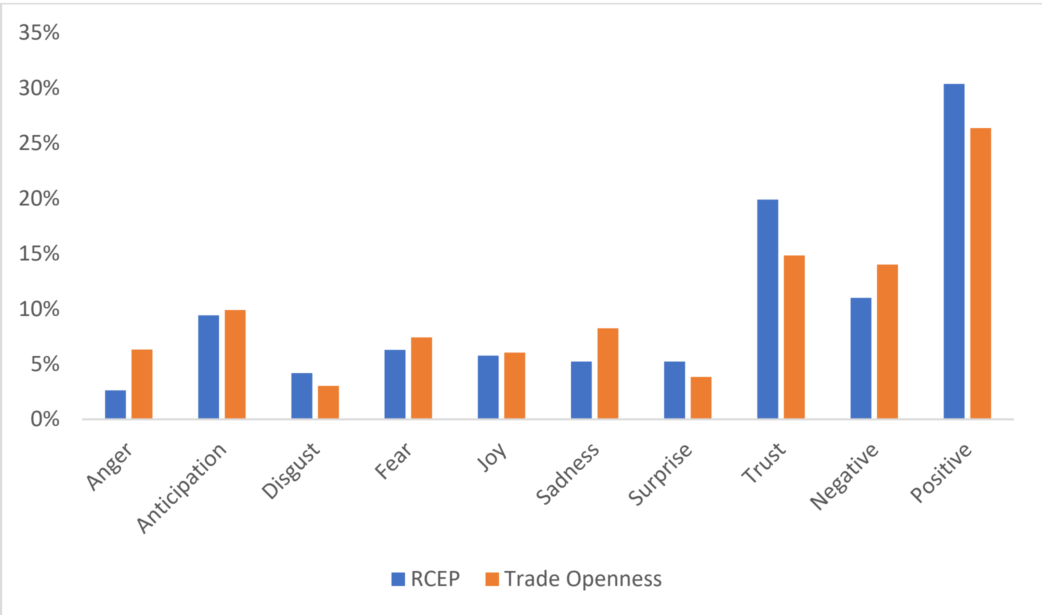


Source: Authors' calculation

The results, especially for the three largest economies, somehow support the results of the awareness and trust ratings survey of Pulse Asia, June 24-27, 2022, which revealed United States as the most trusted, followed by Japan and Australia, while China as the least among the 10 countries included in the survey (Bajo/GMA News 2022). Social Weather Stations has a similar trust rating survey, which also revealed that USA is the top trusted country by Filipinos, followed by Australia and Japan, in 2019, while US and Australia as the most trusted and China remains least trusted, in 2020 (SWS 2019 and 2020).

For RCEP and topics on trade openness (international trade, trade liberalization, trade and economic participation and cooperation, etc.), more favorable sentiments can be observed as indicated by generally more positive and higher trust scores. Positive sentiments more than double as compared to negative sentiments (Figure 10, 11, and 12).

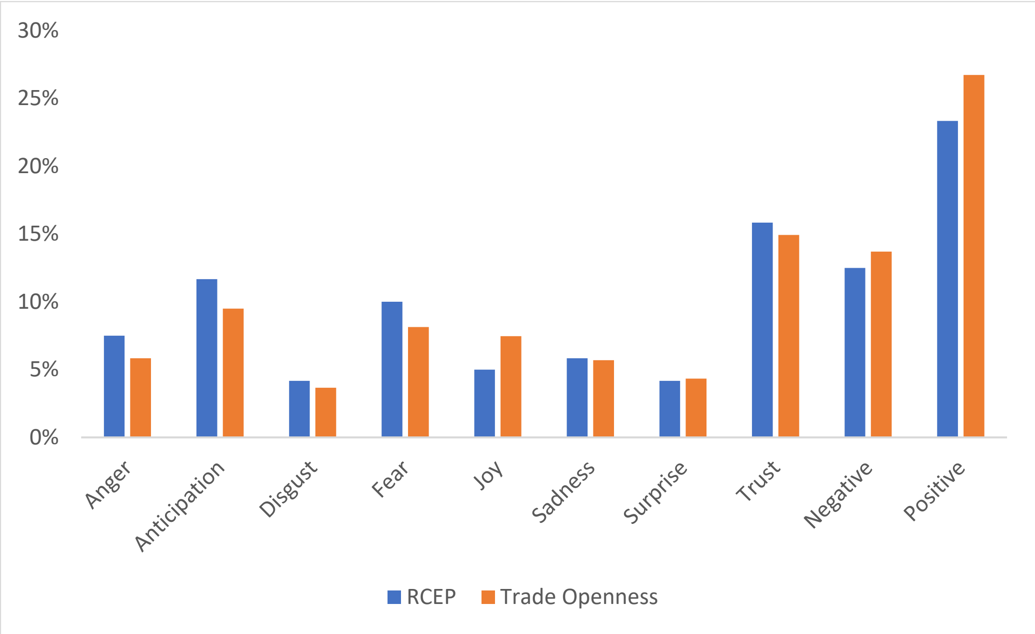
Figure 10. nrc results for RCEP and Trade Openness, tweets



Note: RCEP - Regional Comprehensive Economic Partnership

Source: Authors' calculation

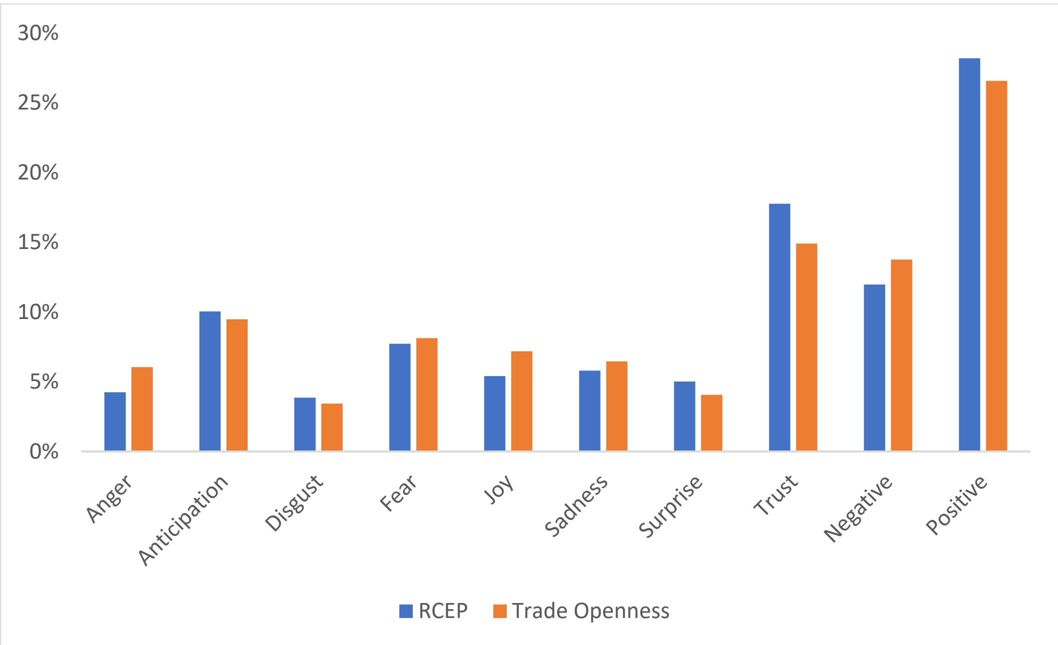
Figure 11. nrc results for RCEP and Trade Openness, online news



Note: RCEP - Regional Comprehensive Economic Partnership

Source: Authors' calculation

Figure 12. NRC results for RCEP and Trade Openness, tweets and online news



Note: RCEP - Regional Comprehensive Economic Partnership

Source: Authors' calculation

In terms of emotion categories, trust also appears to be greater than the rest. It can be noted, however, that next to anticipation, fear does seem to be creating a non-negligible impression on RCEP, which is relatively high as compared to joy.

The number of words detected and categorized in the *nrc* lexicon is presented in Annex 4.

5.3 Word Association

To further highlight some insights, particularly for RCEP and trade openness, terms that are highly associated with the top ten most frequently used words in the texts referring to these topics are determined. Word associations further provide insights on what the most frequent words are all about (Table 11). Unlike purely presenting the list of the topmost frequently mentioned terms, word associations somewhat reveal a more concrete picture of the themes discussed in the texts. In addition, the terms most likely are more interrelated and coherent to the terms they associate with, providing more reasonable information.

Table 11. Terms associated with the top 10 words referring to RCEP

10 Most Frequent Words	Associated Words
trade	free, deal, cours, enforc, fta, agreement, pact, biggest, import, manag, output, communiti, dti, countri, export, asean, mega, philippines, industri, partner, market, global
econom	comprehens, export, import, manag, output, market, fail, philippines, free, countri, deal, ratifi, global, signatori, deepen, facilit, integr, key, postpandem, recoveri, mega
region	comprehens, philippin, export, mega, market, deal, ratifi, countri, particip, fail, access, bloc, commerc, preferenti, import, manag, output
partnership	comprehens, philippin, mega, particip, access, countri, bloc, commerc, preferenti, foreign
senat	ratifi, foreign, order, urg, call, session, import, manag, output
comprehens	partnership, region, econom, philippin, mega, particip, access, bloc, commerc, preferenti, foreign
ratifi	senat, fail, membership, session, account, half, import, manag, output, region, econom, foreign, tackl, philippines, concur
agreement	world, biggest, domest, economicfreedom, trade, free, asean, product, enforc, fta
join	bpo, employ, resili, chinaasean, potenti, forum, partner, rcep, sector
deal	mega, trade, major, export, market, import, manag, output, countri, free, global, particip, access, econom, told, region, strong, philippines, bigger, preferenti

Source: Authors' compilation

Similarly, Table 12, on the other hand, presents the words associated with the most frequently used terms that refer to trade openness.

Table 12. Terms associated with the top 10 words referring to trade openness

10 Most Frequent Words	Associated Words
trade	free, crypto, lend, network, ftas, lft, binanc, agreement, exporter, comprehens, stock
export	perform, lag, rebound, growth, crucial, highvalu, servic, dutyfre, grant, continu, challeng, russiaukrain, broader, fisheri, skorea, strategic, ban, optimist, war, vulner, demand, enterpris, valu
import	sugar, pork, volum, duti, histor, implement, rtl, tariff, fish, highest, worth, reduc, salt, shortag, oil, product, billion, doubledigit, expens, stabil, expensiv
econom	indonesia, chile, comprehens, great, bullish, industri, framework, reaffirm, align, reform, collabor, usph, strengthen, philippinesus, intellectu, asiapacif, singapor
global	chinese, yuan, lag, forecast, index, effect, unctad, posit, rebound, trend, uncertain, coronavirus, economi, demand, covid, weaken
rcep	ratif, comprehens, clarifi, misconcept, senat, prioriti, treati, benefit, ratifi, approv, review, support, align, access, concurr, particip, malaysian, intellectu, properti, provis, urged,industry
invest	exporter, japan, pledg, capit, asia, ftas, ease, direct, promot, pacif, attract, peza, reliant, bounc, barrier, compani
foreign	pledg, ease, ownership, direct, phsaudi, saudi, investor, barrier, bsp, ppp, telco, liber, attract, polici, capit, amend, wage, incom
rice	law, tarif, farmer, tariff, remove, gmo, golden, inflation, farming, organic, support, regulatori, repeal, rtl, import
deal	conclud, free, prefer, canadaasean, gateway, biggest, effect, american, trade, urged

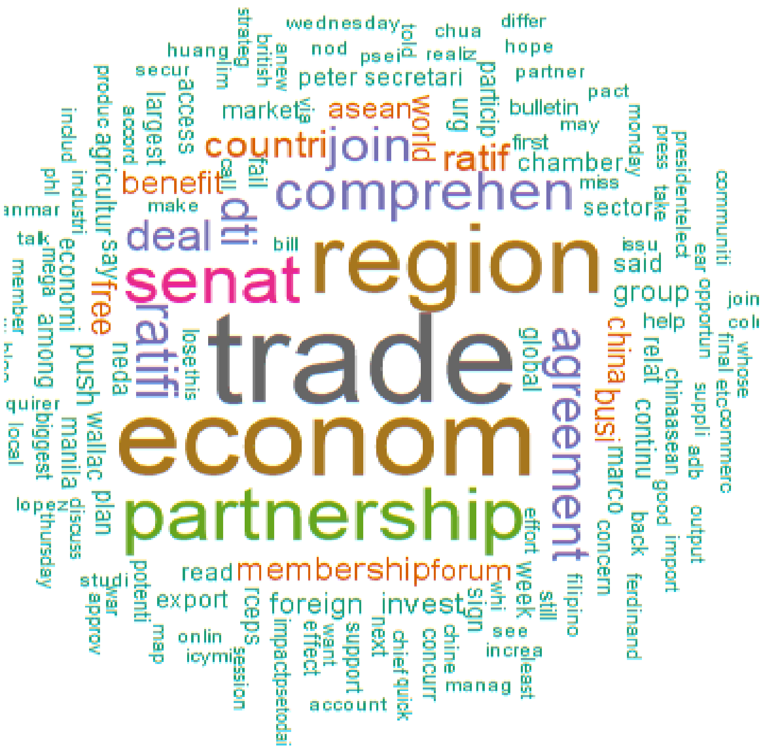
Source: Authors' compilation

5.4 *Word Clouds*

Word clouds are constructed to aid in providing a different perspective on the insights derived from the texts collected (Figures 12 and 13). Word clouds are based on the bag of words, showing how the discussions center around these words. Word clouds give ideas how these topics are discussed based on the relative frequency of mentions, relative to the other topics. Also, the position of the words inside the cloud does not imply anything, however, the size of the texts indicates their relative importance.

Figures 13 and 14 essentially show that concepts or topics are somehow related more related to RCEP and trade openness. For RCEP, for instance, "trade", "economy", "partnership", and "region", among others, appear to be important. Other topics, such as "senate", "ratify/ratification", "agreement", "comprehensive", among others, are also noteworthy in RCEP discussion, which may point out some pressing issues about the bloc during the period. On the other hand, while "trade" and "export" are unquestionably more relevant to trade-openness, other topics such as "investment", "economy", "RCEP", "global", "import", and "rice", among others, also appear to be relatively relevant in the discussion.

Figure 13. RCEP word cloud



Source: Authors' construct

Figure 14. Trade openness word cloud

Source: Authors' construct

6. Conclusion and Recommendations

The paper discusses the use of sentiment analysis on investigating the semantic orientation of tweets and online news towards selected topics. Text mining and analysis are performed to generate information about prevailing issues discussed. Scoring is then conducted to categorize their sentiments using the four commonly used lexicons – *afinn*, *bing*, *syuzhet*, and *nrc*.

The findings suggest that the general perception of the netizens based on the tweets and online news gathered held positive sentiments, suggesting favorable views about the selected countries and topics. Considering the emotions of the texts, the sentiments can be best described as "trust". "Anticipation" and "fear", however, cannot be ignored, which may be reflective of the current global crisis and uncertainties which trade agreements are often associated with.

Particularly for RCEP, the general perception seems favorable. While "trust" prevails for this topic, there are sources of "anticipation" and "fear" that must be addressed; including the Philippines' failure to ratify the agreement. Concerns over this topic must be clarified and the decision to whether ratify or not must be fast tracked as, over time, this may only add up to unnecessary uncertainties and skepticism.

This paper presents the potential of alternative data sources and sentiments as useful indicators to monitor public opinion and perception towards critical national and global issues. The principal finding of this paper underscores the role of public sentiments and opinions that are shaped in response to the fundamental economic, political, and social conditions, and should be given more careful attention in public policy.

This study, however, has several limitations. First, the findings are limited to the viewpoints of individuals at the time of data collection, particularly Twitter users who are not necessarily directly affected by the issues discussed, may only make up a very limited portion of the citizenry, and who may be largely young individuals (i.e., echo chambers). Second, the approach presented in this paper in determining public sentiments do not capture real time opinions. Third, sources of texts and information utilized in this study, particularly Twitter, heavily contain noise and contents arising from the concerted efforts by trolls and fake accounts, who spread information that may alter the "true" public opinion and sentiments. While attempts are made to address and reduce the noise in the dataset, a more objective computational approach to address this is beyond the scope of this paper. Finally, since tweets that contain information about the geographic location of users and tweets are very limited (about 1% of all tweets), this paper utilized only tweets with which the language and location are indicated (i.e., Tagalog, or English and within the Philippines), which further reduces the dimension of the dataset. Acknowledging these limitations, further research is compelled to compromise these limitations.

Furthermore, more careful investigation on the foundations of these sentiments, whether positive or negative, or "trust", "anticipation", or "fear", should be done. Identifying these sources helps improve areas that are favorable, while addressing unfavorable issues. It would also help formulate a strategy for promoting international trade agreements with certain countries.

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Annexes

Annex 1: Coverage of RCEP

Coverage	Chapter
Initial Provisions	1 Initial Provisions and General Definitions
Trade in Goods	2 Trade in Goods 3 Rules of Origin 4 Customs Procedures and Trade Facilitation 5 Sanitary and Phytosanitary Measures 6 Standards, Technical Regulations, and Conformity Assessment Procedures 7 Trade Remedies
Trade in Services	8 Trade in Services
Movement of Persons	9 Temporary Movement of Natural Persons
Investment Business Environment	10 Investment 11 Intellectual Property 12 Electronic Commerce 13 Competition 14 Small and Medium Enterprises 15 Economic and Technical Cooperation 16 Government Procurement
General Provisions	17 General Provisions and Exceptions 18 Institutional Provisions 19 Dispute Settlement 20 Final Provisions

Source: Compiled based on the legal text of RCEP Agreement (rcepsec.org 2019)

Annex 2: Summary of changes in export demand from the Phillipines to RPCs post-RCEP

RPC	Positive Effects (in USD Thousand)	Negative Effects (in USD Thousand)	Net Effects (in USD Thousand)
South Korea	134,713.27	(46,055.73)	88,657.54
Malaysia	39,454.87	-	39,454.87
Myanmar	2,258.89	(14.72)	2,244.17
Indonesia	11,290.55	(1,797.69)	9,492.86
Viet Nam	6,969.95	(4,178.75)	2,791.20
Cambodia	1,824.69	-	1,824.69
New Zealand	865.93	(0.22)	865.71
Australia	697.38	(0.03)	697.35
Singapore	-	-	-
Brunei	-	(0.31)	(0.31)
Lao PDR	-	(2.91)	(2.91)
Japan	21,906.58	(29,902.81)	(7,996.23)
Thailand	3.36	(39,261.23)	(39,257.87)
China	9,846.17	(72,751.98)	(62,905.81)

Note: Calculations based on the results of WITS' SMART simulations; Mirrored analysis where changes in PH exports are estimated when RPCs eliminate tariffs on imports from other RPCs; used 2019 base trade data, except for Cambodia (2016), South Korea (2018), Malaysia (2016), and Thailand (2015); HS combined nomenclature; RPC = RCEP participating countries; USD = US Dollar

Source: DTI (2019)

Annex 3: Effects of changes in export demand to the Philippines

RPC	GDP Effects (in PhP M)	Output Effects (in PhP M)	GDP Effects (in PhP M)	Household Income Effects (in PhP M)
South Korea	11,187.03	19,966.18	246,467.00	8,877.17
Malaysia	712.61	1,758.94	14,129.00	526.34
Myanmar	626.87	1,087.50	14,206.00	441.33
Indonesia	588.22	2,096.67	11,869.00	412.63
Viet Nam	446.99	1,194.65	9,877.00	334.57
Cambodia	78.43	366.25	1,557.00	50.98
New Zealand	60.35	140.48	1,149.00	44.30
Australia	32.21	73.58	749.00	25.21
Singapore	30.31	70.77	656.00	23.22
Brunei	-	-	-	-
Lao PDR	(0.02)	(0.04)	-	(0.01)
Japan	(0.14)	(0.34)	(3.00)	(0.11)
Thailand	(735.47)	(1,600.32)	(11,620.00)	(513.77)
China	(996.87)	(2,673.83)	(20,875.00)	(737.08)

Note: Calculations based on the results of WITS' SMART simulations and SAM Multiplier Tool; Used the changes in export demand for top 10 commodities (6-digit HS codes) due to tariff elimination, from SMART simulations, as exogeneous shock to the SAM Multiplier Tool; PhP = Philippine Peso

Source: DTI (2019)

Annex 4: Number of words categorized in *nrc* lexicon

a. Tweets

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive
Australia	52	97	24	50	75	37	38	135	99	209
Canada	37	88	24	54	78	43	41	116	89	185
China	49	73	27	59	51	42	33	94	111	175
Indonesia	69	121	34	81	94	63	65	152	146	276
Japan	81	138	45	111	115	93	69	193	179	355
Korea	25	55	14	32	37	22	24	61	62	114
Malaysia	46	85	15	50	50	41	27	97	91	182
Thailand	57	105	21	68	83	51	57	116	126	213
USA	132	199	95	171	179	127	95	301	272	50
Vietnam	67	99	29	71	82	64	57	125	144	225
RCEP	5	18	8	12	11	10	10	38	21	58
Other Topics	23	36	11	27	22	30	14	54	51	96

b. Online News

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive
Australia	10	9	2	11	6	7	5	14	11	25
Canada	7	15	5	11	10	9	6	25	19	40
China	11	13	0	12	7	5	3	13	16	22
Indonesia	2	10	1	3	5	1	2	15	4	24
Japan	4	14	3	14	3	4	2	14	14	30
Korea	9	16	0	8	8	6	6	20	16	37
Malaysia	5	7	0	8	5	3	2	5	12	18
Thailand	11	18	0	10	10	4	5	12	15	28
USA	5	12	2	10	7	1	3	25	13	27
Vietnam	3	11	0	5	3	3	2	10	7	22
RCEP	9	14	5	12	6	7	5	19	15	28
Other Topics	43	70	27	60	55	42	32	110	101	197

c. Tweets and Online News

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Surprise	Trust	Negative	Positive
Australia	57	100	26	57	79	42	41	140	107	219
Canada	35	86	23	53	69	43	36	123	86	189
China	57	78	27	65	54	46	35	97	121	187
Indonesia	69	125	34	81	97	63	65	161	146	287
Japan	82	144	46	115	116	95	70	196	186	362
Korea	30	67	12	32	43	24	28	76	68	134
Malaysia	49	88	15	55	52	44	28	99	101	189
Thailand	59	111	21	71	86	52	59	121	131	226
USA	136	200	97	174	179	127	95	306	279	509
Vietnam	77	109	30	82	90	71	64	139	165	253
RCEP	11	26	10	20	14	15	13	46	31	73
Other Topics	58	91	33	78	69	62	39	143	132	255

Source: Authors’ construct