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Computational Analysis on Twitter Users' Attitudes towards COVID-19 Policy Intervention

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Abstract

During the initial period of the COVID-19 pandemic, governments around the world implemented non-pharmaceutical interventions. For these policy interventions to be effective, authorities engaged in the political discourse of legitimising their activity to generate positive public attitudes. To understand effective COVID-19 policy, this study investigates public attitudes in South Korea, the United Kingdom, and the United States and how they reflect different legitimisation of policy intervention. We adopt a big data approach to analyse public attitudes, drawing from public comments posted on Twitter during selected periods. We collect the number of tweets related to COVID-19 policy intervention and conduct a sentiment analysis using a deep learning method. Public attitudes and sentiments in the three countries show different patterns according to how policy interventions were implemented. Overall concern about policy intervention is higher in South Korea than in the other two countries. However, public sentiments in all three countries tend to improve following implementation of policy intervention. The findings suggest that governments can achieve policy effectiveness when consistent and transparent communication take place during the initial period of the pandemic. This study contributes to the existing literature by applying big data analysis to explain which policies engender positive public attitudes.

Keywords: *COVID-19, legitimisation, policy intervention, public attitude, sentiment analysis, Twitter*

1. INTRODUCTION

COVID-19 (SARs-CoV-2) has continued to infect individuals worldwide since its discovery on December 31, 2019. Without a clear treatment or vaccination for this novel virus upon its initial recognition, governments around the world had to implement other policies to control the damage inflicted by COVID-19. Policy responses to the COVID-19 pandemic have ranged from economic measures such as tax payment deferrals and business loans, to social distancing measures including travel restrictions and lockdowns [1, 2].

Even though the specific policy responses to the COVID-19 pandemic are diverse among countries, their primary goal was to save lives and restrain the spread of the infection. Thus, the COVID-19 policy intervention shows a tendency to achieve this goal [3]. In the initial period of the pandemic, the unavailability of pharmaceutical interventions led to the worldwide implementation of non-pharmaceutical interventions (NPIs), measures taken by individuals or communities to limit the person-to-person spread of the virus and reduce the risk of personal infection. Examples of NPIs include social distancing, lockdowns, travel restrictions, isolation,

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and school closures [4]. This study focuses only on NPIs among variety of policy interventions.

However, policy interventions have varied in their timing and stringency [1, 5]. Countries such as South Korea and Singapore implemented strong policy interventions in the initial stages of the pandemic [1, 6]. Canada was swift in implementing containment measures, whereas Sweden and the United States were not [7]. The initial responses of Ukraine, Israel, and Germany were stringent, whereas France, Japan, and India took less stringent measures [8]. Scholars have attempted to explain these differences based on government structure, institutional characteristics, government ideology, societal characteristics, public interaction, trust, and leadership [2, 6, 9-12]. They demonstrate that each country's different contexts—including culture, public response, and institutions— influence policy choice and their success or failure.

Public compliance is crucial for ensuring effective policy intervention. Therefore, policy intervention includes authority participating in political discourse to legitimise the process. Especially in the COVID-19 situation, compliance generated by the legitimisation process within political discourse is important for achieving policy goals, as NPIs issued in response to the pandemic have been restrictive and intrusive [13, 14]. Without high levels of compliance, public intervention is hardly effective. The level of public compliance with policy intervention has varied by country [15, 16]. Studies have found that interpersonal trust, trust in government, personal beliefs, cultural characteristics, and societal characteristics affect public compliance and voluntary actions [17-20]. In addition, the level of compliance is associated with how policies are implemented. Zimmermann, et al. [16] have shown that compliance motivated by rule following results in legislating rules and suggests that homogeneous enforcement of policy intervention is impossible. This coincides with An and Tang [6] insistence that the successful strict COVID-19 policy intervention in East Asia would not be applicable in other countries.

As public compliance generated by legitimisation is important for understanding policy intervention's success or failure, previous studies have attempted to identify public compliance by investigating public attitudes [17, 20, 21]. For example, Toll and Li [22] have found that public attitudes affect compliance with vaccination policies. Positive attitudes toward vaccination and vaccine acceptance are associated with compliance with vaccine policies. Most advanced research focuses on social media analysis as an effective method to measure public attitudes. Specifically, scholars have utilized social media data to understand public attitudes during the COVID-19 situation [23-26]. However, most studies have been limited to a certain timepoint or country. Furthermore, there is a lack of research on public attitudes from the perspective of effective policy intervention considering authorities' legitimisation within political discourse.

2. THEORY

2.1 COVID-19 Policy Intervention and Its Effectiveness

Intervention is generally defined as an interference that would modify a process or situation [27]. Interventions are often classified based on the extent to which they intrude on individuals' freedoms and responsibilities. Public health policy intervention ranges from simply providing information to legislating strict rules [28].

In the initial stages of COVID-19, governments around the world had to implement NPIs to reduce person-to-person contact and minimize transmission due to an absence of vaccines or efficient treatments [1, 29]. The application of NPIs varies from government guidelines or advice to mandatory enforcement [20]; however, for contagious disease, key interventions have taken the form of restrictive measures [30]. Confronted with the COVID-19 pandemic, most governments have implemented highly intrusive NPIs, such as travel restrictions, social distancing, lockdowns, school closures, and mandatory facial coverings [13].

However, COVID-19 policy intervention varies in its timing and stringency by country. Countries have implemented policy interventions at different timepoints [1, 5]. While some countries such as South Korea (SK), Canada, Singapore, and Hong Kong responded swiftly to the situation, countries such as Belgium, Spain, the United Kingdom (UK), and the United States (US) were criticized for their slow responses [1, 7]. The US and Sweden's early COVID-19 policies were not containment policies, in contrast to many other countries' implementation of social distancing and extensive lockdowns [7]. The stringency of countries' initial responses varied widely. Countries like Ukraine, Israel, and Germany took stringent first response policies. However, France, Japan, and India took less stringent first response policy [8].

Previous studies have yielded insights into countries' diverse COVID-19 policy interventions, proposing various influential factors. Capano, et al. [1] have found past experience and preparedness for pandemics to be relevant factors. Trust is also crucial factor for policy intervention as Cairney and Wellstead [10] insist that trust in scientific experts, fellow citizens, and the government are significant. Moreover, previous studies have suggested that government centrality and effectiveness, freedom, and government structure [2]; demography [12]; and institutional and cultural differences [6] affect intervention of policy.

SK, the UK, and the US have shown different patterns in COVID-19 policy intervention. SK was one of the East Asian countries to implement stringent COVID-19-related policies [6]. Being one of the early infection sites, SK has been praised for stabilizing death rates with massive testing and digitally based contact tracing in the initial stages of the pandemic [31]. Organizational learning from previous experiences with infectious disease outbreaks—such as MERS and SARS—has led to effective COVID-19 countermeasures [1, 6]. Moreover, Asian governments' authoritarian tendencies and collectivistic culture contribute to enhanced public action and voluntary compliance [6, 13].

The UK received harsh evaluations of its initial COVID-19 policies. Hunter [32] demonstrates that the government response was vague, irrational, and unscientific. Further, Maor and Howlett [33] point to the government's limited attention span, especially before March 16 when government policy suddenly reversed course. The UK government enacted more stringent policies only after high death rates were expected by the scientific community [34, 35]. Cairney and Wellstead [10] insist that the UK's government policy has been consistent with scientific experts' advice; however, there were still criticisms that the government did not accept a wider pool of advice.

The US has become one of the countries most affected by the virus, with the highest confirmed cases and deaths since April 2020. Scholars argue that vagaries of federalism leading to disjointed responses across the nation and a lack of national coordination and leadership have worsened the situation [1, 36, 37]. Moreover, the inability to secure testing kits caused problems in assessing the seriousness of the situation [36, 37]. This resulted in an inability to maintain constant testing rates [36].

The effectiveness of COVID-19 policies has been evaluated by the effective reproduction number, death count, or number of cases [5, 7, 38]. In the initial stages, speed of policy implementation was critical [39]. Countries that enacted policies early on achieved success, regardless of the strictness of their final policies [7]. For example, Australia, Japan, and SK, which implemented quick responses, showed better results compared to Spain and Belgium, which were relatively late in their initial responses. Various NPIs (e.g., containment policy) are also effective in limiting the spread [7, 38]. Containment policies such as social distancing have been successful in "flattening the curve" [38]. However, Liu, et al. [40] have insisted that containment policies are effective only to the extent that the public complies with them.

2.2 Legitimisation of COVID-19 Political Discourse and Public Compliance

Political discourse involves political actors communicating about political matters for a political purpose [41]. It is a kind of decision-making process where actors legitimise certain actions or beliefs, which shapes people's thoughts and attitudes. Legitimisation refers to "the right to be obeyed," thus, the legitimisation process justifies political action [42]. It is usually done by authorities who lead political discourse through communication measures such as speech and text [43, 44]. Legitimation strategies, for example congruence and consistency, are considered important in forming legitimacy within the discourse [44]. The public accepts political decisions with a positive attitude, in other words positive compliance attitude, when the legitimisation is convincing [45]. Legitimisation is especially important in the context of the early Covid-19 pandemic because most countries depended on coercive measures implementing restrictive policy intervention including NPIs.

Multiple studies research legitimisation within political discourse during Covid-19. Nikolopoulou and Psyllakou [43] analyse the legitimisation process undertaken by the Greek government to initiate public compliance. Bélanger and Lavenex [44] found that both the communication on domestic mobility and international travel were flawed in political communication strategies to legitimise the mobility policy. Considering political discourse, many scholars focused on the authorities that lead the political discourse according to traditional top-down understanding. However, empirical evidence showed that public attitude is also important to understanding acceptance of the legitimacy process within political discourse as well as the authorities' communication. In particular, since a positive the public attitude established by an effective legitimisation strategy leads to better public compliance, public attitude must be understood.

Voluntary public compliance is one of the crucial factors impacting the success of restrictive policy intervention [40]. Compliant behaviours are a combination of material, emotional, and normative goals at play [46]. Previous literature has demonstrated the importance of compliance when enforcing restrictive policies [17, 19]. Especially in democratic countries, restrictive interventions are difficult to enforce because NPIs are socially and economically disruptive [14]. Research regarding NPIs also suggests that community acceptance must exist for it to be effective [47].

Various studies have identified factors influencing compliance with COVID-19 restrictions. Murphy, et al. [48] suggest that the normative concern of duty played a key role in Australians' compliance with COVID-19 policies. They also demonstrate that compliance stems not from force but from the public understanding of responsibility. Al-Hasan, et al. [49] also point out the importance of persuasion in securing people's compliance. Other factors have also affected public compliance during the pandemic. Internal factors include self-concern [17, 19], trust in political leadership [19], belief in the effectiveness of health precautions [17], level of information, threat perception [50], and feelings of commonality [16]. External factors include length of time experiencing restriction [48] and consistent messaging [18].

Public attitudes are a key factor to study in terms of individuals' compliance and health-related behaviours , since positive public attitude represents the successful legitimisation of the authorities' political discourse [45]. Toll and Li [22] examined the relationship between public attitudes and behaviours concerning the Measles, Mumps, and Rubella (MMR) vaccine. They showed that positive attitudes toward vaccination and vaccine acceptance are usually associated with full uptake, neutral attitudes with partial uptake, and negative attitudes with non-vaccination. Xu, et al. [51] surveyed Chinese individuals to understand the relationship between attitudes and four NPIs, which include handwashing, proper coughing habits, social distancing, and mask wearing. This study found positive attitudes to be a strong predictor of implementing NPIs.

To analyse the possibility of public compliance, previous studies have often utilized survey methods. Altmann, et al. [21] conducted a survey to investigate public support for contact tracing apps in France, Italy, the UK, and the US. The results showed that those with less trust in their national government are more hesitant to use these apps. In a similar vein, Clark, et al. [17] conducted a worldwide survey about the beliefs contributing to compliance. They found that belief in the efficacy of health behaviour could increase compliance. Concerning the study of COVID-19, Wang, et al. [20] applied the theory of reasoned action (TRA) to understand the motivation behind individuals' compliance with preventive measures in the US and Canada. The results showed age, political ideology, and satisfaction with the government to be related to levels of compliance.

However, scholars point out the limitations of survey approaches to investigate the possibility of public compliance [17]. The biggest drawback is a lack of historical understanding and personal bias because surveys can result in a lack of responses from intended participants. Furthermore, respondents may hide inappropriate behaviours or experience difficulties judging their own behaviours [52].

Recently, there have been attempts to overcome the limitations of survey approaches. Scholars focus on social media to evaluate public attitudes and perceptions, and find the impact of social media on health communication [24, 53]. Social media is advantageous for collecting large quantities of publicly accessible data over multiple years [53]. Due to these merits, analysing data from social media is effective in investigating public attitudes, public perceptions of regulations, and risk perception. Moreover, social media altered the dissemination process of discourse by blurring the line between authors, consumers, and gatekeepers of information [54, 55]. This complicates the public's acceptance process legitimisation within political discourse, which makes research on social media data necessary [55]. Previous studies have used data from Twitter, Reddit, or YouTube comments and employed various methods, such as qualitative document analysis and content analysis [24], sentiment analysis [25], and topic modelling [26].

While existing studies present an overview of public perceptions or attitudes during a certain timeframe in a certain country, comparative studies of public attitudes during pandemic situation among various countries are not sufficient. Public expressions on social media platforms are an excellent source of data for understanding individuals' attitudes, as they include personal support, beliefs, and perceptions within the frame of public discourse in the social media community. Moreover, social media data contain aggregated individual opinions at the precise moment as huge data. In this regard, this study focuses on social media to investigate public attitudes toward COVID-19 policy intervention.

This study examines the question of how public attitudes reflect COVID-19 policy intervention using a comparative analysis of big data collected from Twitter. Based on previous literature, Figure 1 presents the conceptual framework for policy intervention, public attitude, and policy effectiveness, and The dotted line represents the focus of this study. Through the legitimisation process within the political discourse, governments' policy intervention can be justified. Public attitude reflects the success or failure of the legitimisation strategy. If the persuasion process of legitimising is effective, public attitude will be positive, if not, negative. This will ultimately result in increased or decreased public compliance, leading to high and low policy effectiveness. This study focuses on the public attitude presented in social media that represents whether government authorities conducted an adequate legitimisation process. Negative or positive public attitudes can be investigated by applying big data analysis and machine learning techniques.

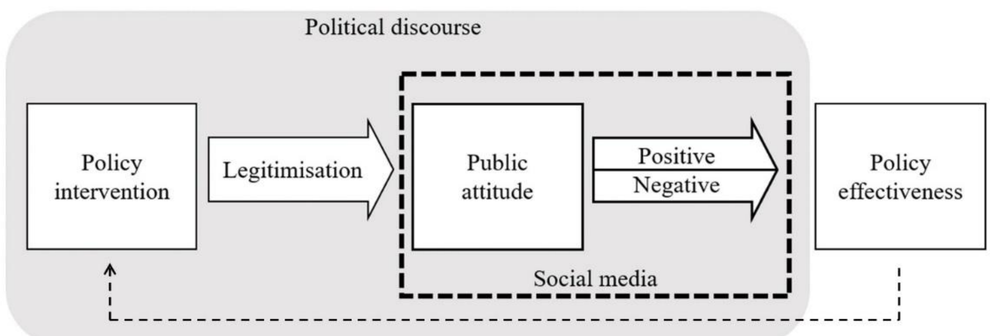


Figure 1. Conceptual framework

We focus on the initial period of the COVID-19 pandemic in three democratic countries: SK, the UK, and the US. All three countries had their first confirmed cases at the end of January. From December 2019 to March 2020, SK was the only East Asian country to have significant rise in confirmed cases, except for China. The UK and US also showed a significant rise in confirmed cases. Despite similarities in the infection timing and its expansion during the first few months, the countries are different geographically, culturally, and governmentally. By investigating public attitudes (as conveyed on social media) and policy intervention in various countries, it is possible to understand whether and how public attitudes reflect COVID-19 policy intervention and find evidence of the successful legitimisation process. Empirical evidence of the relationship between policy intervention and public attitudes has implications for effective policymaking in the COVID-19 era.

3. MATERIALS AND METHODS

3.1 Research Period Selection: Measuring Stringency Level of Policy Intervention

This study investigates stringency level to better understand changes in policy intervention in SK, the UK, and the US based on the Oxford COVID-19 Government Response Tracker (Oxford Tracker) [56]. This is important for selecting a meaningful research period for our big data analysis of public attitudes. If there are sharp changes in the stringency level, then the periods in which such changes occurred are considered as important and require further analysis to understand the situation.

We calculate stringency level by summing 10 indicators selected from the Oxford Tracker [3] between January 1, 2020, and November 30, 2020, where Higher stringency level scores indicate stricter policy intervention. The Oxford Tracker classifies policy response to COVID-19 into 23 indicators as of September

29, 2021. This presents the strictness of government responses in a cross-national, cross-temporal manner. The indicators are divided into five groups: containment and closure, economic response, health system, vaccine policies, and miscellaneous. To calculate stringency level, this study employs indicators related with restrictive policy intervention, which indicates non-pharmaceutical intervention, from Oxford Tracker [57].

Figure 2 shows the stringency levels of three countries' policy intervention and their changes during the initial stages of the COVID-19 pandemic. The red box represents the selected research period. During this time, most countries had limited knowledge about the virus and thus experienced confusion in attempting to implement appropriate countermeasures. The figure represents significant divergence in stringency levels in SK, the UK, and the US, whose initial COVID-19 policies' timing and strictness differed. Based on changes in stringency levels, we select four significant periods. The first period is from January 22 to February 4, when significant changes in stringency level occurred in SK. Moreover, this was when the first confirmed cases were announced in the UK and US. The second period is from February 20 to March 4, in which there was a significant increase of stringency level in US for the first time and a second stage of increase in SK. From March 9 to 22, US maximized its stringency level, and the UK began taking a more stringent approach to match other countries' efforts. The last period is from April 17 to 30, in which SK relaxed its policy intervention, while the UK and US maintained the highest stringency level.

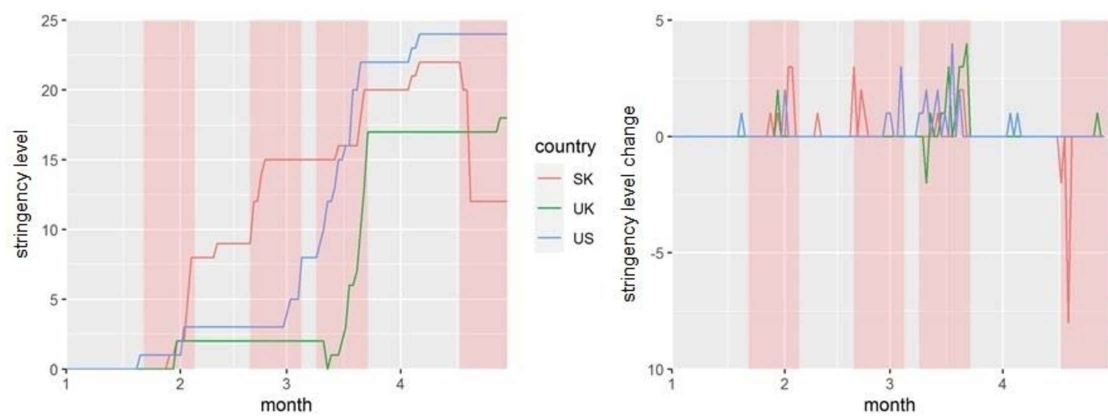


Figure 2. Changes in stringency from January 1, 2020, to April 30, 2020

3.2 Big Data Analysis of Public Attitudes Toward Policy Intervention

We conduct big data analysis to identify differences among the three countries' public attitude during the four selected research periods. We utilize social media (Twitter) data, which have the big data characteristics of volume, variety, velocity, and veracity (4V's) [58]. A tweet is an unstructured combination of text, picture, or video, 500 million of which were shared per day on Twitter in 2014 [59]. However, the quality and accuracy of tweets are uncertain [60]. Therefore, three steps are essential for big data analysis: web crawling, preprocessing, and data analysis.

Web crawling. Web crawling is the process of downloading linked page off the web locally. This is usually the first step in web mining tasks [61]. We focused on Twitter because it is a representative social networking service (SNS) that plays a prominent role in sociopolitical events. Previous studies have also examined tweets and their interaction [62].

This study crawls data from the Twitter Full-archive Search API and extracts them from the Twitter server using Python. This study applies "Requests" module in Python, which sends an HTTP request to the Twitter server that returns tweets according to the query. We extract tweets based on four queries: (1) tweets including the words "corona," "covid," or "코로나" ("corona" in Korean); (2) tweets only with original text (excluding retweets); (3) tweets written in Korean or English; and (4) limiting geographic location to SK, the UK, or the US. Then, we collect tweets over four research periods: January 22 to February 4, February 20 to March 4, March 9 to 22, and April 17 to 30. Each period consists of 14 days, with each day containing a maximum of 500 datapoints per country. The total number of tweets collected is 81,598, and the total number of tweets of one country per one period is approximately 5,000 to 7,000.

Preprocessing. As many scholars have highlighted [63, 64], preprocessing is an essential step for analysing big data as tweets include noise, such as URLs (https://), hashtags (#), @ symbols, emojis, and incomprehensible language. Such noise not only makes the tweets difficult to analyse but also may yield less accurate results.

We delete tweets with unclear geographical locations, using only tweets that clearly identifies the UK, the US, or SK as their location. Next, we exclude tweets if the meaning of the word "corona" is irrelevant to COVID-19. There are many irrelevant tweets about Corona beer, the Corona airport plane crash, and an area in California with the name Corona, as well as or tagging someone whose name is Corona, in the first period (January 22-February 4) particularly. We delete URLs, hashtags, @ symbols, emojis from the text. Concerning sentiment analysis's effectiveness, there are mixed opinion on whether preprocessing, such as stop-words, spell checking, and lemmatization, is efficient [65]. Therefore, we create models based on both preprocessed and unprocessed data and select whichever one demonstrated better accuracy. Table 1 shows the final number of tweets in each period.

Table 1.Number of tweets

	UK		US		SK	
	Total	Analysed	Total	Analysed	Total	Analysed
Period 1 (January 22-February 4)	6,713	5,747	7,000	5,969	4,887	4,558
Period 2 (February 20-March 4)	6,998	6,286	7,000	6,474	7,000	6,625
Period 3 (March 9-March 22)	7,000	6,350	7,000	6,522	7,000	6,665
Period 4 (April 17-April 30)	7,000	6,532	7,000	6,645	7,000	6,682

Data analysis. Data analysis consists of two steps. First, we compare public attitudes and each country's historical timeline of COVID-19 policies. We estimate public concern and its variations based on changes in the volume of tweets mentioning topics relate to policy intervention; thus, we count the relevant tweets and evaluate the level of public concern in each period. Countries' historical timelines show significant changes in policy intervention and COVID-19-related events. By comparing the variations of public concern about policy intervention with the historical timelines, we can understand how policy intervention and Covid-19 related events affect the public concern.

We apply the six categories presented in Table 2. Utilizing 10 indicators from the Oxford Tracker [56], we derive four categories: "social distancing", "stay at home", "contact tracing", and "mask". "Close public transport", which is C5 in the Oxford Tracker, is excluded from further analysis because none of the three countries enforced closures public transport. Moreover, we include the two additional categories of "individual right" and "government" considering the agent and its impact of policy intervention during the COVID-19 pandemic. Policy intervention tends to infringe on "individual right," and "government" is crucial for grasping public concerns toward the agents of policy intervention, including government authorities and public officials. "Individual right" includes personal privacy individual right, and freedoms. "Government" involves public attitudes toward the government, which implements and supervises public compliance with regulatory responses.

Second, we analyse public sentiment using the collected tweets to comprehend the public acceptance by the legitimisation of the policy intervention. We analyse tweets related to COVID-19 in general and then analyse tweets related to policy intervention specifically. Sentiment analysis judges the overall sentiment of a text—negative, positive, or neutral. [66]. There are a variety of sentiment analyses, such as multi-class or multi-label analysis, ranging from words to sentences to full documents. This study focuses on binary sentiment classification, which sorts sentiments in a tweet into negative or positive categories. This is due to its abundance in training sets for model training, especially in Korean.

Sentiment analysis can utilize two different methods: lexicon and machine learning. The lexicon method classifies the sentiment of a document according to predetermined values of words and rules. In the machine learning method, the rule is set by the computer itself rather than by the researcher. There are many machine learning algorithms that can be used for sentiment analysis, including naïve Bayes (NB) classification, support vector machines (SVM), and deep learning methods. We apply the deep learning method; it is advantageous in that it can perform representation learning. Moreover, experts consider deep learning as a great model for classifying resource-poor language [67]. Especially because the natural language processing (NLP) research on Korean is thin compared with that on English, deep learning has its advantages.

We adopt the Convolutional Neural Network (CNN) method for the deep learning process. Originally, the CNN method is intended for image classification, leaving the Recurrent Neural Network (RNN) method for text analysis. However, since Kim [68] suggested the use of CNN for sentence classification, it has been widely used. This method yields higher accuracy compared with other machine learning algorithms and high performance when combined with Global Vectors for Word Representation (GloVe) embedding [69]. Our CNN model is a binary classification with accuracy of 86.33% in English and 85.68% in Korean using GloVe embedding. We use unprocessed data for the CNN model because the model trained with unprocessed data is more accurate than the model trained with processed data. The models trained using processed data yielded accuracies of 84.68% (English) and 84.43% (Korean).

Table 2. Categories of policy interventions

Category	Definition	Oxford Tracker's category of policy intervention
Social distancing	Tweets related to social distancing NPIs, such as school or work closure, restrictions on mass gathering, cancellations of public event, and restrictions on domestic and international travel.	C1 School closing C2 Workplace closing C3 Cancel public events C4 Restrictions on gatherings C5 Close public transport C7 Restrictions on internal movement C8 International travel controls
Stay at home	Tweets related to staying at home, lockdown, and quarantine.	C6 Stay at home requirements
Contact tracing	Tweets related to contact tracing.	H3 Contact tracing
Mask	Tweets related to mask or facial protection.	H6 Facial coverings
Individual right	Tweets related to privacy, individual right, and personal freedom	
Government	Tweets related to the government, NHS (National Health Service), CDC (Centres for Disease Control and Prevention), or the KCDC (Korea Centres for Disease Control and Prevention).	

4. RESULTS AND DISCUSSION

4.1 Volume of Tweets Related to COVID-19 Policy Intervention

Figures 3, 4, and 5 are visualizations of the volume of tweets in each country, showing tweets from each category in each period. Moreover, we include important events concerning the COVID-19 pandemic and related policy implementation during the research periods, assigning a letter to each.

Figure 3 shows the volume of tweets related to policy intervention in SK. SK had its first confirmed case on January 20 (a), which was about 10 days earlier than the other two countries [70], and SK maximized its alert level (level 4) on February 24 (c) [35]. This was due to the mass infection in Daegu caused by a Shincheonji religious ceremony [70, 71]. The numbers quickly escalated to more than 5,000 confirmed cases by the end of the second period, March 4 (d) [72]. On March 22 (e), the government decided to maintain strong social distancing measures for precaution during the third period [72]. The government finally relaxed social distancing measures beginning April 20 because the daily new confirmed cases dropped below 50 for over 10 days (f) [72].

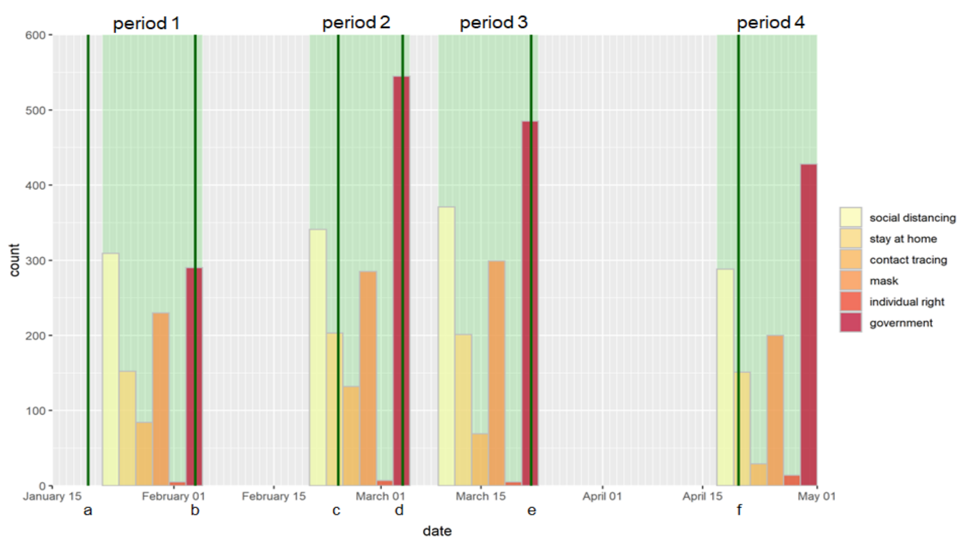


Figure 3. Volume of tweets related to policy intervention: SK

The X-axis and Y-axis indicate dates of important historical events and the number of tweets, respectively. The green boxes indicate the four research periods. The histograms within the green boxes represent tweet volume of each category in each period. The letters indicate important events: a. first confirmed case (January 20), b. travel restrictions (February 4), c. COVID-19 alert level 4 enacted (February 24), d. 5,000 confirmed cases (March 4), e. stronger social distancing measures (March 22), f. weaker social distancing measures (April 20)

In SK, over 10% of tweets concern specific policies: “social distancing,” “stay at home,” “contact tracing,” and “mask.” Specifically, 13.5%, 15.3%, 14.8%, and 10.2% for the first, second, third and fourth periods. Compared to the UK and the US, SK’s public concern about policy intervention is relatively higher during the first period. Except for ‘contact tracing’, public concern was the highest in the third period over “social distancing,” “stay at home,” and “masks.” The third period was the peak of SK’s policy intervention’s stringency according to Figure 2. This shows that public concern increases in tandem with the seriousness of the pandemic situation in the country. SK implemented digital contact tracing in the initial stages, but public concern about “contact tracing” is lower than other categories [31]. There is strong public concern over “mask” even though SK had no official mask mandate during the research period [72].

Interestingly, the volume of tweets about "individual right" is unremarkable, indicating scarce public discussion of this aspect despite the stringent policy intervention. On the other hand, the public are more concerned with the "government," with this category amassing the greatest number of tweets in three of the four periods. This result indicates strong public concern for the government and their action. The public was most concerned about the "government" in the second period when government increase the COVID alert level to the highest [35].

As Figure 4 shows, the UK had its first confirmed case on January 31 (a) [71]. Then, the UK government advised self-isolation on March 12 (b) [73]. Only after the third period, the UK government issue a stay-at-home order on March 23 (d) [73], while both the US and SK implemented stay-at-home orders and strong social distancing measures during the third period. This difference is also visible in Figure 2, as UK's policy intervention was the last to reach peak stringency level. Moreover, the UK's confirmed cases exceeded 5,000 on March 18 (c), which was also the last among the three countries [73]. However, this increase in cases happened following the increase of tests the week before [73]. Therefore, the accuracy of UK's confirmed cases was open to doubt, as Jit et al. [74] note that only 1% of infection was detected up until March 23. On April 7, confirmed deaths in the UK surpassed 1,000 (e) [75].

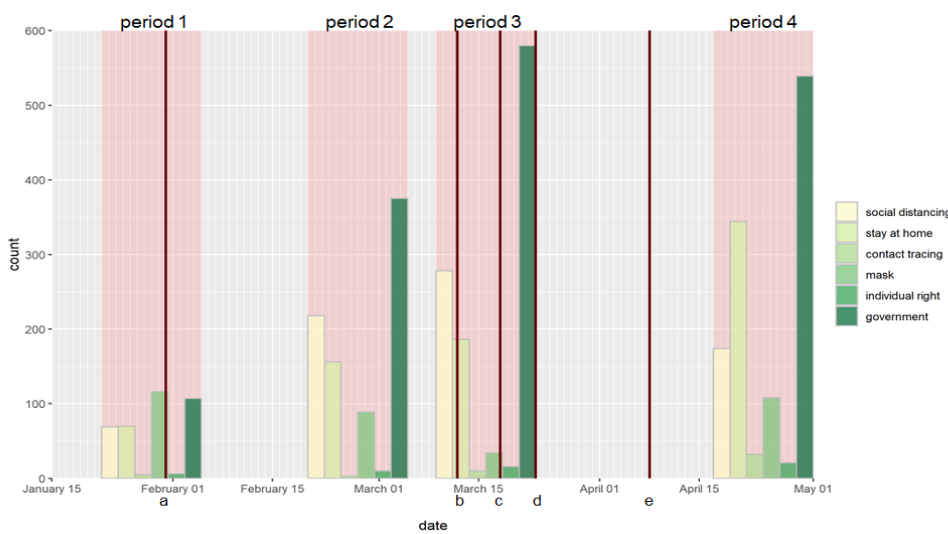


Figure 4. Volume of tweets related to policy intervention: UK

The X-axis and Y-axis indicate dates of historical events and the number of tweets, respectively. The red boxes indicate the four research periods. The histograms within the red boxes represent tweets volume of each category in each period. The letters indicate notable events: a. first confirmed case (January 31), b. government stay-at-home advice (March 12), c. over 5,000 confirmed cases (March 18), d. government stay-at-home order (March 23), e. new deaths surpassed 1,000 (April 6)

The lack of public concern in the first period compared to other periods indicates low awareness of the COVID-19. This tendency could also be a result from delayed increase in cases and in stringency level of policy intervention. Trends in public concern over the four categories, 'social distancing', 'stay at home', 'contact tracing', and 'mask' are irregular. Public concern about "social distancing" and "stay at home" increase over time. Before the government issued the stay-at-home order on March 23 (d), public concern was highest for "social distancing" until the third period; however, public concern about "stay at home" was the highest in the fourth period. This implies that policy intervention receives increased attention when it is enforced extensively. Public concern about "contact tracing" was relatively low throughout the period, even though Public Health of England contact traced cases until March 12 [76]. Such low concern could be a result of the UK's low capacity, dealing with five people per week before it halted [77]. The trend in the volume of tweets about "mask" is irregular, and there were fewer tweets than in SK. This may be because a mask mandate was not implemented in the UK during the research period.

There is also little concern about “individual right” despite policy intervention’s restriction thereof. This aligned with the trend in SK. Lastly, public concern about the “government” is the highest throughout the second, third, and fourth periods, but especially during the third period when the government implemented major policy interventions. This result indicates that the in the UK, the public have strong concerns about the government in general while showing a lack of interest in specific policy intervention.

Figure 5 presents the trends in the US. The US had its first confirmed case on January 30 (a) [78] and reached 5,000 confirmed cases by March 17 (b) [75], only one day earlier than the UK. Like the UK, the US also had controversies concerning case detection. The testing capacity in the US was quite limited early on, which is why most states recommended the test to those who had travelled to affected countries [79]. There were also criticisms of faulty testing kits and delayed results [37]. Within one week after reaching 5,000, the confirmed cases increased to over 34,000 (d), and the US was recognized as the third-most infected country in the world [80]. During this surge of cases on March 19 (c), California was the first state to issue a stay-at-home order [81]. Unfortunately, the US had the highest death rate in the world by April 11 (e) [82]. Overall, the increase in US policy intervention’s stringency was later than in SK but earlier than in the UK.

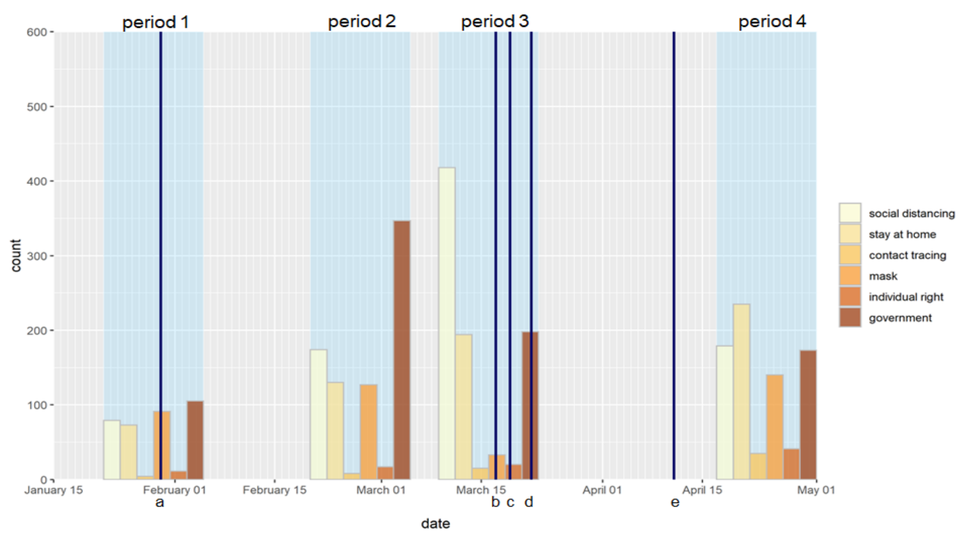


Figure 5. Volume of tweets related to policy intervention: US

The X-axis and Y-axis indicate dates of historical events and the number of tweets, respectively. The blue boxes indicate the four research periods. The histograms within the blue boxes represent tweets volume of each category in each period. The letters indicate notable events: a. first confirmed case (January 30), b. over 5,000 confirmed cases (March 17), c. first state-issued stay-at-home order (March 19), d. 34,896 confirmed cases (March 22), e. highest death toll in the world (April 11)

The volume of tweets is relatively lower than in the other countries. Notably, only “social distancing” generated significant interest in the third period, which aligned with implementation of various social distancing measures such as school closures [83] large event bans [84], and travel restrictions [85]. Public concern over “stay at home” increases throughout the period; however, there is no drastic increase of concern in this category despite states issuing stay-at-home orders beginning on March 19. Public concerns over “contact tracing” and “mask” are also low and exhibit irregular trends.

We also found low public concern about “individual right.” This result shows that while some policy interventions infringed on individual rights considerably, these did not drive public opinion. Furthermore, the volume of tweets about the “government” is the smallest among the three countries, while in SK and the UK public concern about “government” comprise the highest volume of tweets compared to the other categories. (The average number of tweets about the government in the three countries are as follows: SK 437, UK 400.25, and US 205.75.) This may reflect the historical background of federalism in the US, as policy intervention at the state level are more influential than those emanating from the central government [37]. Moreover, unlike in SK or the UK, public concern about the "government" does not coincide with the increase in policy intervention. This also suggests the US public's lack of concern about policy intervention.

4.2 Sentiment Analysis

Based on the analysis of the volume of tweets, we can better identify public attitudes toward COVID-19 policy intervention. This raises questions about how the public responds to policy intervention and what degree of public compliance and acceptance of the legitimisation process we can ultimately expect. To address these questions, we conduct sentiment analyses for all tweets and each category over the four periods to grasp positive and negative emotions. Figures 6 and 7 show the results of the sentiment analysis. Each graph represents a kernel density estimate for each country (country names on left) in each period (numbers at top). Higher positions on the Y-axis indicate greater probability of high density. The X-axis represents a spectrum of sentiment ranging from 0 to 1 ("negative" to "positive"). The lines connection the peaks of negative sentiment ($\leq$0.25) and positive sentiment ($\geq$0.75) for each period. This shows overall trends in sentiment. The percentages are the ratio of negative sentiment ($\leq$0.25) to positive sentiment ($\geq$0.75) within each dataset

Figure 6 displays the results of the sentiment analysis including all tweets. While SK show a neutral distribution throughout the whole period, the UK and US present similar distributions of strong negative sentiment. Regarding SK, positive sentiment increases and transforms the graph more neutral as the pandemic proceeds, showing relatively less emotional responses to the issue. This is interesting because SK is one of the countries to quickly implement stringent regulatory response [1, 6, 7]. Patterns in the UK and US is similar until the second period, displaying strong negative sentiment. However, trends in the UK and US diverge in the third and fourth periods. While there are no significant differences in sentiment in the UK between the third and fourth periods, in the US negative sentiment continuously decreases and positive sentiment continuously increases until the fourth period. In other words, the gap between negative and positive sentiment continues to decrease in the US until the last period. This is surprising considering the faster timing of overall policy intervention in the US compared to the UK according to the stringency level as shown in Figure 2. This implies that countries with faster implementation of policy intervention tend to exhibit better public sentiment. Despite some differences, the three countries show similarity in negative sentiment decreasing and positive sentiment increasing over time. Comparing the fourth period with the first period, SK, the UK, and the US respectively show 5%, 18%, and 23% decreases in negative sentiment and 8%, 8%, and 13% increases in positive sentiment.

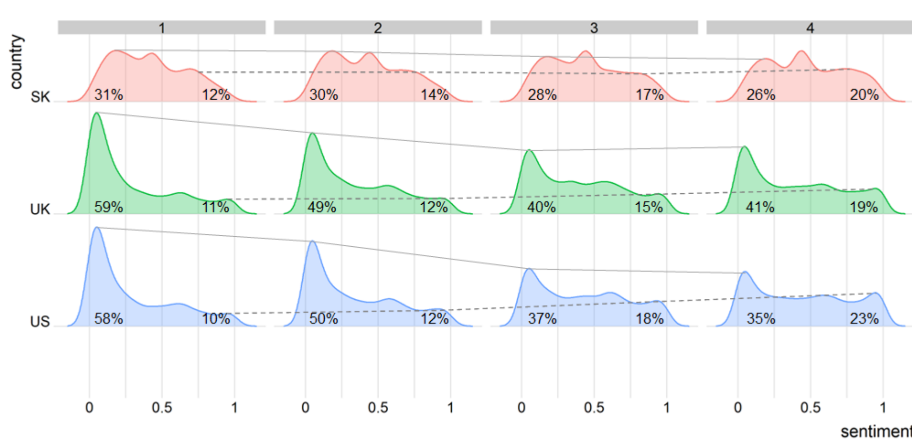
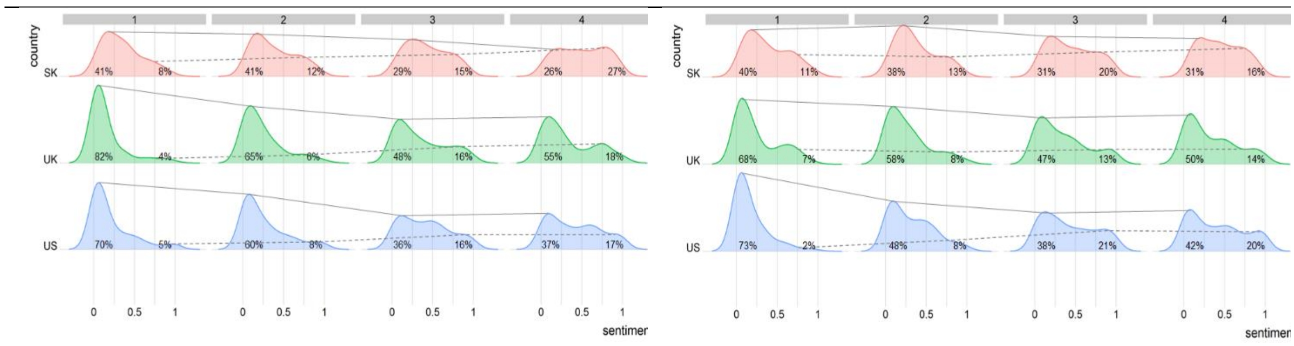
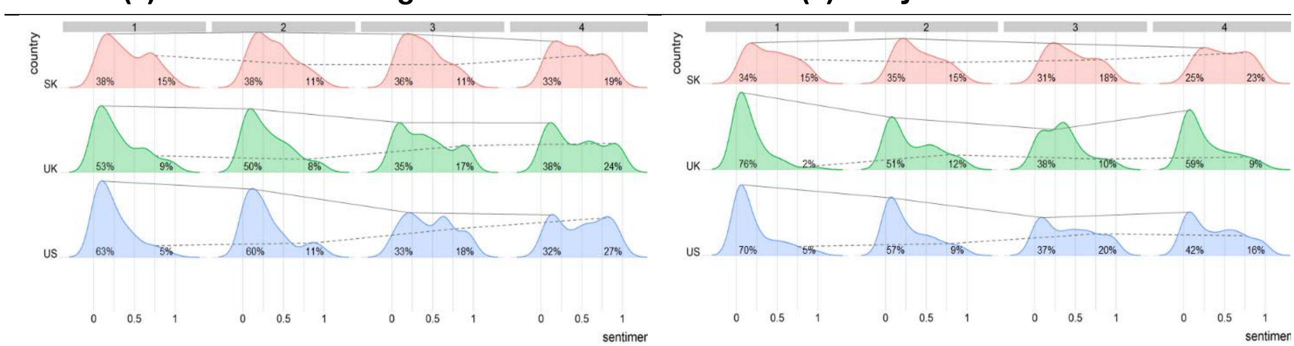


Figure 6. Sentiment analysis of all tweets

Figure 7 presents the results of the sentiment analysis across categories for each country and period. Overall, the results show quite different patterns according to country and category. The Figure 7(a) presents sentiments regarding “social distancing.” Tweets about “social distancing” carry negative sentiments in the UK and US, while in SK they are relatively neutral. The gap between positive and negative sentiment in SK is 1% in the last period. The UK and US show an 8~10% increase in positive sentiment after policy implementation in the third period, and negative sentiment is lower in the fourth period than in the first period. However, even after implementation of social distancing measures, the UK shows a 7% increase in negative sentiment from the third period to the fourth period. It is noteworthy that in the sentiment analysis across the categories, we exclude “contact tracing” and “individual right” due to insufficient sample size. For “contact tracing,” the UK an US have less than 10 sentiment datapoints each. Such small samples cannot represent reliable sentiments and attitudes about that category. For “individual right,” none of the three countries has considerable number of related tweets. The low volume of tweets risks generalizability issues.



(a) “social distancing” tweets **(b) “stay at home” tweets**



(c) “mask” tweets **(d) “government” tweets**

Figure 7. Sentiment analysis of each tweet

The result of sentiment underlying “stay at home” tweets also indicate greater negativity in the UK and US than in SK. SK’s sentiment toward “stay at home” is similar to that toward “social distancing” during the first period, but there is 5% higher negative sentiment and 11% lower positive sentiment in the last period for “stay at home” compared to “social distancing.” However, the gap between positive and negative sentiment is still small compared to those in the UK and US. For this category, UK had 5% lower negative sentiment and 5% higher positive sentiment relative to the US in the first period. However, the UK’s negative sentiment decrease less than in the US during the second through fourth periods. Negative sentiment in both the UK and US show a slight increase in the fourth period after the implementation of stay-at-home orders. However, negative sentiment in the UK and US is lower in the fourth period compared to the first period.

Next, the results of the sentiment analysis of tweets about “mask” in SK shows few changes compared to tweets from the other categories. Both negative and positive sentiment change within a range of ±5% from the first period. Although SK shows strong concern over mask based on the analyses in section 3.1, the underlying sentiment is similar to that in the UK and US, especially during the third and fourth periods. This is interesting considering claims in previous research that mask is more accepted in collectivistic cultures [86]. The UK and US's "mask" data are not consistent. Approximately 30 words are collected for the third period. In the UK, overall sentiment about "mask" is 10% less negative than it was in the US during the first and second periods. However, during the third and fourth periods, the US shows a sharp decrease in negative sentiment and sharp increase in positive sentiment. This could be due to changes in expert and government recommendations. During late March, public health experts, such as Scott Gottlieb, suggested that the public should consider wearing masks [87]. On April 3, the CDC announced its recommendation for all Americans to wear face masks to prevent the spread of COVID-19 [88]. In the last period, the US exhibited the most neutral sentiment about "mask" among the three countries.

Lastly, the sentiment underlying tweets about "government" in SK shows a more neutral pattern compared with the other categories, while sentiments in the UK and US are more negative. Neutral sentiment toward the "government" implies that SK's public attitudes is less skewed. SK's sentiment was most neutral in the fourth period, with a 2% gap between negative and positive sentiment, after the government announced relaxation of policy intervention April 20. The UK showed consistently low positive sentiment and high negative sentiment toward "government." It is interesting that there was a sudden rebound in negative sentiment in the fourth period. This reflects sudden changes in policy due to harsh criticisms from scientists and medical professionals [33-35]. Beginning in the third period, there was a 10% increase in positive sentiment in the US, compared to a 2% decrease in the UK. This reflects the fact that major policy intervention in the US took place during the third period as presented in Figure 2, including school closures [83], large event bans [89], and stay-at-home orders [81].

4.3 Discussion

In cases of unexpected economic and social disruption such as the COVID-19 pandemic, it is difficult for governments to accurately expect public compliance due to drastic changes in circumstances and a lack of information. As a result, governments attempt to implement diverse policy interventions in response to COVID-19. On the one hand, SK implemented strong policy intervention from the initial stages of the pandemic [6]. On the other hand, the UK government accepted the science advisor's counsel and postponed social distancing measures for as long as possible [90]. The government feared that the public would respond to such policies with fatigue and noncompliance [76, 91].

This study's results show that despite initial differences in public attitudes, the public sentiments of all three selected countries tended to improve after implementation of COVID-19 policy interventions implemented. The effect of policy intervention on public attitudes is made clear by comparing the UK and US. Sentiments toward policy intervention in these countries are similar during the first two periods (strong negative sentiment and weak positive sentiment). However, likely due to the faster implementation of policy intervention in the US, public sentiment eventually became more positive than in the UK. To improve policy intervention's effectiveness, government should consider how they can promote positive public attitudes to secure compliance from the outset. Nevertheless, our findings demonstrate the possibility that governments can eventually engender positive public attitudes irrespective of initial attitudes toward policy intervention.

The results are in line with previous studies that adequate political discourse of authorities generates public acceptance. In particular, effective legitimising strategies of political discourse increase trust. Bélanger and Lavenex [44] discuss that along with the timeliness of the information, proper strategies that engender trust toward information providers legitimises crisis communication.

The empirical evidence from our big data approach has important implications. First, government should provide the public with more consistent messaging to promote and sustain positive attitudes. Benham, et al. [92] have found inconsistent public health messages to be one of the significant factors leading to lack of trust in authority, and such a lack of trust often results in lower compliance [15]. In the result of sentimental analysis, the UK exhibits a resurgence in negative sentiment during the fourth period due to inconsistent messaging in the third period, which was when the UK enacted sudden policy changes [33]. On March 12, specifically, the UK's prime minister announced the "mitigation" policy [73], accepting the inevitability of an outbreak and attempting to minimize suffering [71]. This approach was officially supported by the government's Chief Scientific Advisor [76]. However, the UK government faced harsh criticisms from scientists and medical professionals [35], and a report published by Imperial College stated that epidemic suppression was the only viable strategy [34]. Within four days, the UK government introduced its "suppression" strategy aimed at reducing infection to zero [71, 73]. Both the US and SK show more positive sentiments during the UK's rebound in the fourth period. Even though the US was also criticized for its lack of consistency in government messaging [93], its overall policy did not take a sudden turn as did that of the UK. SK was evaluated as having consistent messaging over media platforms [94].

Second, government should promote transparent communications to foster positive public attitudes. Previous studies demonstrate that transparent communication is a crucial factor in gaining public trust [95, 96]. Regarding "mask," SK exhibit a larger gap between positive and negative sentiment during the second and third periods; however, sentiment improves and stabilizes in a more neutral position during the fourth period. During the second and third periods, SK had a mask shortage [97], and the lack of supply caused price increases. Consequently, some questioned the government's ability to respond [98] before the government eventually disclosed relevant data and began providing timely online service. Kim [97] also defends this argument, with around half of survey respondents identifying the government's transparency as a reason for their satisfaction. There were discussions about the importance of transparent communication from the government in the UK and the US [76, 99].

The characteristics of each country's public attitudes can affect the degree of compliance with policy intervention [17, 22, 51]. In SK, public concern about policy intervention is relatively consistent and high, and public attitudes toward these COVID-19 policies from the sentiment analysis in the SK is more positive compared to in the US and UK despite SK's government having implemented more stringent policy intervention. Both the UK and US exhibit more negative sentiment and lower interest in these policies relative to SK. Moreover, the US did not show a significant increase in public concern about the policy intervention even after their implementation. In April, both the UK and US had anti-lockdown protests [71, 84]. While the protest in the UK was comparatively small, the protests in the US spanned multiple states [71, 100]. Considering that there was no such event in SK, it shows that public attitudes (as revealed by sentiment analysis) can predict public compliance to a certain degree.

5. CONCLUSION

This study investigated public attitudes toward early COVID-19 policy intervention in SK, the UK, and the US to understand such intervention's effectiveness. Our findings show that despite some differences among these countries, it is possible for governments to improve public attitudes when proper policies are implemented with effective strategies to legitimise the procedures. The study also shows that legitimisation strategies to engender trust are important, especially in the initial stages of pandemic in attaining public compliance and achieving policy effectiveness.

Our study makes two key contributions. First, it provides an important explanation of which legitimisation strategy encourage public compliance by analysing the relationship between policy intervention and public attitudes. Our results highlight the importance of consistent and transparent communication. We also discovered that attitudes are crucial in securing compliance and that they should be considered to ensure effective policy implementation. Moreover, this study is one of the few to implement big data and machine learning techniques to analyse public attitudes. Based on this technical approach, we were able to examine a wide range of public attitudes and compare their trends.

Despite its important academic and technical implications, the study has several limitations. We collect data from only the initial stages of the COVID-19 outbreak; thus, the findings may have been affected by the research period and may not be entirely generalizable. Additionally, the data are limited to three countries (SK, the UK, and the US), and the findings are dependent on these countries' socioeconomic characteristics. As for technical limitations, neural network analysis is dependent on the training material. Accordingly, while the model's accuracy is generally quite high, it has limitations in detecting context, such as sarcasm and ambiguous sentences. Next, we should not overlook a lack of research on Korean in the field of natural language processing. Particularly, the labelled training data for Korean was insufficient compared with that for English. Furthermore, Korean is an agglutinative language, whereas English is an analytic language, making Korean a more complex form to analyse.

This study expands our understanding of public attitudes toward COVID-19 policy intervention by applying big data analysis. Future studies would benefit from analysing tweets more meticulously using topic modelling, as well as by using intent analysis prior to sentiment analysis. This would allow the researchers to describe public opinion with greater precision. Moreover, complex analysis would be possible if researchers analyse various public sentiments, such as anger, fear, happiness, and sadness. Lastly, incorporating data from other platforms such as Facebook or YouTube could also provide meaningful results and implications.

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