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Evaluating the Impact of COVID-19 on People's Perception of Travel Safety by Analysing Tweets

Master's Thesis (15 ECTS)

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Evaluating the Impact of COVID-19 on People's Perception of Travel Safety by Analysing Tweets

Abstract:

The COVID-19 pandemic not only cost human lives but also harmed industries like tourism which adds valuable contributions to the GDP of many countries. The pandemic affected global tourism in several ways, such as fewer flights, cancellations, lockdowns and restrictions, etc. This thesis studies COVID-19's impact on people's perception of travel safety leveraging sentiment analysis. Travel-related social media data was collected from Twitter and divided by the severity of the pandemic and the tweets volume of the regions to study the impact and patterns. For analysing data, a RoBERTa-base pretrained sentiment analysis model for tweets was employed. Sentiment scores over time were compared to understand the general trends. Although most of the tweets were neutral, there was an evident change in the proportion of negative tweets to positive. A word frequency was also verified during different periods in this work. Virus-related words were frequently used in positive and negative tweets. The study reveals that people cancelled or postponed their trips due to risks caused by the pandemic.

Keywords:

Machine learning, sentiment analysis, natural language processing, COVID-19

CERCS:

P176 Artificial intelligence

COVID-19 mõju hindamine inimese reisiohutuse tunnetusele läbi tviitide analüüsi

Lühikokkuvõte:

COVID-19 pandeemia mitte ainult ei võtnud inimelusid, vaid kahjustas ka tööstusharusid nagu turism, mis moodustab paljudes riikides suure osa SKTst. Pandeemia kahjustas globaalset turismi mitmel viisil, nagu näiteks lendude vähenemine ja tühistamine, piirangud jne. Käesolev magistritöö uurib inimese tunnetust reisiohutusele, kasutades selleks tundeanalüüsi. Reisimisega seotud andmed on kogutud Twitterist ja on jagatud pandeemia tõsiduse ja volüümi järgi gruppidesse, selleks et uurida nende mõju ja mustreid. Töös kasutati RoBERTa baasil eeltreenitud mudelit. Saadud tulemusi võrreldi ajas, et näha, milline on üldine trend. Kuigi enamus teksti lahterdati neutraalseks, oli näha COVID-19 negatiivset mõju. Selleks, et hinnata pandeemia mõju, võrreldi ka sõnade esinemissagedust. Viirusega seotud sõnu kasutati sageli nii positiivsetes kui negatiivsetes tviitides. Uurimistulemustest selgus, et inimesed tühistasid või lükkasid oma reise pandeemia tõttu edasi.

Võtmesõnad:

Masinõpe, tundeanalüüs, loomuliku keele töötlus, COVID-19

CERCS:

P176 Tehisintellekt

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Introduction and Motivation

In late November 2019, the first case of COVID-19 was detected in Wuhan, China. A month later, the World Health Organization[1] (WHO) declared the virus outbreak a public health emergency of international concern [1]. The virus kept spreading worldwide from person to person, and the most effective way to stop the virus was to avoid close contact with humans. Therefore, in almost every country, various restrictions and rules had to be set to reduce the spread of the virus. Several restrictions were established, such as complete border closure, suspension of flights, and destination-specific travel restrictions [2]. Over 100 countries worldwide imposed partial or complete lockdowns by the end of March 2020 [3].

The pandemic not only cost human lives but also harmed different industries. As safety concerns are a primary factor in tourists' willingness to travel [4], the tourism industry can be adversely affected by crises or disasters [5] and influenced by many factors that a traveller cannot control such as political instability, economic conditions, natural disasters, weather, etc. [6]. Taking into account these unavoidable factors, a key research trend in tourism involves risk and crisis management [7] which includes infectious diseases [8], [9]. As a consequence of COVID-19, one of the industries which got strongly affected by COVID-19 was tourism. Some countries rely strongly on tourism as it represents over 20% of their GDP (Gross Domestic Product) [10]. Compared to 2019, the coronavirus caused a 72% decline in international tourist arrivals in 2020 and 71% in 2021. It represents a [11]2.1 billion USD loss in international arrivals in both years combined. As a result, export revenues from international tourism lost 2.1 trillion USD in the two years of the pandemic [12].

Besides economic loss, COVID-19 also shaped the people's mindsets. Before the pandemic outbreak, nobody could imagine social isolation or a travel ban. Li *et al*. (2020) proposed in their studies that due to COVID-19, the tourist behavioural pattern has also changed [13]. In the context of travel, taking into account the changes in mindset of people during COVID-19, we analysed social media posts to study the change in people's perceptions over time. To this aim, we collected social media posts (i.e., tweets) from Twitter and leveraged an existing sentiment analysis model to analyse the posts.

The primary aim of this master's thesis is to investigate how the COVID-19 pandemic impacted perception towards travel safety. The data for this work was collected from Twitter, because it is a popular platform with a worldwide user base. The data has been divided into pre-COVID-19, pre-lockdown, lockdown and post-lockdown to understand the trends and changes in one's mindset and behaviour. People have experienced different variations of COVID-19 over time; because of this, the collected data has also been analysed by its seasonality. During the beginning of COVID-19 and the lockdown period, people were more actively writing post-COVID-19-related content.

By using machine learning, tweets have been given sentiment scores standing for positive, neutral or negative. By analysing the scores and keywords, the patterns have been analysed. With this work, the following hypothesis is proposed:

- People's perception of travel safety has decreased due to COVID-19, and they are re-evaluating their travel motivations due to the current risks.

Based on above mentioned hypothesis, we investigate the following research questions:

RQ1. What factors influence travel risk perception during the COVID-19 pandemic?

[1] https://www.who.int

RQ2. How does COVID-19 affect peoples' views of "travel insurance"?

Analysing people's views toward insurance can provide additional knowledge of safety perception because insurance provides protection against risks, and any subsequent consequences, such as flight cancellation and medical cover.

The rest of the thesis is organised as follows: Chapter 1 focuses on tourist behavioural changes and sentiment analysis. Furthermore, the technique employed in this work is presented; Chapter 2 introduces the related works done regarding researching COVID-19 pandemic impacts; Chapter 3 explains which methodology has been used in this thesis; In the last part, the results are presented and analysed.

1. Background

On November 17, 2019, the first case of COVID-19 was detected in Wuhan, China [14]. Besides material losses, pandemics can evoke serious anxiety [13]. Traditionally, epidemics have been considered to be among the most important deterrents to travel because they increase safety and security concerns among tourists [15].

The COVID-19 pandemic has definitely left its mark and reshaped the person's mindset and risk appetite. In tourism, perceived risk is subjective and can affect travel destination choices and travel behaviour. Li *et al.* [13] derived six risk perception attributes from a psychological distance: health, psychological, social, performance, image and time risk.

Li *et al.* (2022) [13] categorised in their research focusing on COVID-19 tourist's behavioural changes and suggested that tourists will express three tendencies in their behavioural patterns:

1) from general to elaborate - 'general' tourist refers to tourists who travel for general purpose but not for specifically detailed one. Due to COVID-19, tourists might become more elaborate and narrow down their travel choices. Therefore, travellers who are more concerned about their health risks might cancel their trips. Image risk can affect a traveller's destination choice. Due to increased psychological, social, performance and time risks, travellers would be deliberate in their decision and choose locations that satisfy their specific motivations.
2) from open-hearted to closed - open-hearted is someone who is kind, and also, it is similar to being 'friendly'. On the other hand, closed might stand for someone unwilling to accept outside influences or new ideas and has a negative attitude when interacting with others. Due to COVID-19, travellers may travel with smaller groups and with people they know, such as family members or close friends. In addition, people tend to be more careful regarding others' health and make decisions based on that. For example, instead of shared transportation, people might prefer private one.
3) from radical to conservative- tourism requires a person to accept a certain level of risk. Tourists are likely to modify their behaviour to mitigate a risk if they believe there is a threat of COVID-19 [13].

In this work, we analyse Twitter text data regarding travelling and travel safety during pre-covid, pre-lockdown and post-lockdown. Sentiment and word frequency analysis have been conducted. By analysing travel and COVID-19-related tweets, we are studying the direct impact of the pandemic towards travelling. Labelling text by sentiment facilitates understanding the individual's affection towards certain topics. Furthermore, we would like to learn if an individual's behaviour indicated any changes described in Li *et al.*(2022) [13] due to COVID-19.

1.1 Sentiment Analysis on Social Media Posts

Social networks are popular for sharing data and ideas. The amount of data generated in 30 seconds on the Internet is about 600 GB of traffic. In 2006 Jack Dorsey, Evan Williams, and Biz Stone created Twitter. It was developed as a microblogging system and can be defined as a real-time information network that connects people to the latest information. More than 320 new accounts are created, and more than 98,000 tweets are posted on the Twitter platform every minute. These reasons make the analyses of Twitter data a significant domain for business intelligence and marketing. The typical age of Twitter users ranges from 14 to 60 years and is equally distributed by both genders. Therefore, sentiment analysis (SA) has become a powerful tool to analyse opinions on Twitter [16]. Furthermore, Twitter is one of the most popular sites for extracting information for SA.

SA is not limited to one application. Therefore, it ranges from business and marketing, politics and health, to public action. It can be applied to world events such as sports or disasters. For example, it can identify the needs of people during a disaster and discover locations of disease outbreaks. Furthermore, it can play an important role in decision-making [16].

Whilst there are several approaches to conducting SA (as shown in Figure 1.), we used a machine learning approach in this thesis.

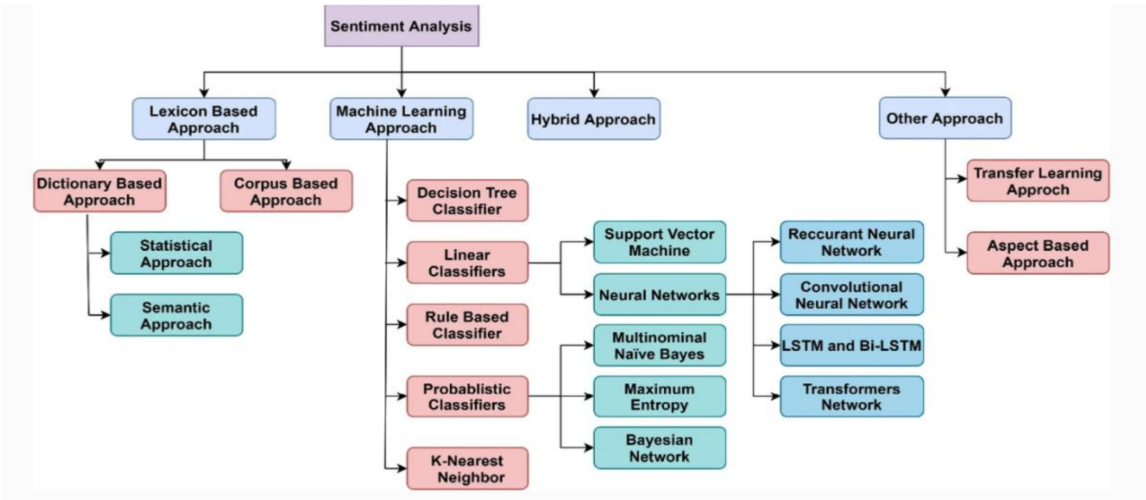

Figure 1. Methods of sentiment analysis [17].

According to literature, SA is mainly carried out in three levels: document level, [11], [18], sentence level [19], [20] and aspect-level [21], [22]. Informal short social media text like tweets presents stiff challenges to SA such as data sparsity (irregular and ill-formed text), data dynamics, etc. In social media posts like tweets, SA is applied at the sentence level. Each tweet can be considered as a sentence and the sentiment analysis process assigned a polarity score to the entire tweet. However, researchers also proposed SA on the aspect level for tweets [21]. In this thesis, we applied SA to our collected tweets at the sentence level and obtained a polarity score for each tweet.

1.2 RoBERTa

We used a transformers-based model for evaluating the polarity of the text (in our case, the textual content of the tweets) in this thesis. The Robustly Optimized BERT Pretraining Approach (RoBERTa) is based on Google's Bidirectional Encoder Representations from Transformers (BERT). The BERT model does not use decoder layers. The masked tokens are in the attention layer of the encoder. $\text{BERT}_{\text{BASE}}$ contains a stack of N=12 encoder layers, $d$model = 768 and can also be expressed as H=768. A multi-head attention sub-layer contains A=12 heads and the dimension of each head zA remains 64 as in the original Transformer model [23].

$$d_k = \frac{d_{model}}{A} = \frac{768}{12} = 64$$

$\text{BERT}_{\text{BASE}}$ [23]

RoBERTa has the same architecture as BERT; however, it uses a byte-level BPE as a tokeniser (same as GPT-2) and uses a different pre-training scheme [24] To create RoBERTa, BERT has been modified as follows: the model has been trained longer, the next sentence prediction objective has been removed, longer sequences have been trained, and the masking pattern applied to the training has been dynamically changed [25].

2. Related Work

COVID-19 impacts on tourism and everyday life have been researched in various studies. Mansoor *et al.* (2020) [26] presented COVID-19's impact on online learning and working-from-home scenarios in their work. They used sentiment analysis to understand the general opinion of the people. The data was collected from Twitter and then labelled using the lexicon VADER. For sentiment analysis, classification models such as LSTM and ANN were used. Their exploratory analysis shows that people are rather neutral regarding coronavirus and more positive regarding working from home and online learning. Besides learning about sentiments, they also conducted emotion analyses.

Leelawat *et al.* (2022) [27] used sentiment analysis for English-language Twitter data to learn about tourism in Thailand during the COVID-19 pandemic. Besides ranking their data as positive, neutral and negative, they also labelled it by intention. Machine learning algorithms such as CART, Random Forest and Support Vector Machine (SVM) were used. To gain insights, the top 10 words in each sentiment and intention class were analysed. Moreover, the data was also categorized by location. From the study, by analysing the top 10 words, they discovered that Twitter users have positive sentiments toward food, tourist destinations, and hospitality in Thailand but negative sentiments toward the Thai political situation and the COVID-19 pandemic.

In 2022, Carvache-Franco *et al.* [28] published an article regarding the topic and sentiment analysis of crisis communication about the COVID-19 pandemic in Twitter's tourism hashtags. They used popular tourism hashtags to collect data from Twitter. SentiStrength, a lexicon made up of 2310 words obtained from the Linguistic Inquiry and Word Count (LIWC) was used for sentiment analysis. The results show that the crisis communication revolved around the global impact and effect of the COVID-19 pandemic on the tourism industry. The sentiment of the tweets showed that the topics in the discussion were rather positive which supports the effectiveness of the crisis communication. Furthermore, crisis communication exhibited a difference between the genders in the main topics and in the evaluation of the text sentiment of the tweets.

COVID-19's impact on tourism has been also studied by using other methodologies besides social media data analysis. Villac´e-Molinero *et al.* (2021) [2] explored the new travel risk scenarios by analysing risk perception during the pandemic. They conducted an online survey with data collected from 1075 travellers residing in 46 countries and interviewed 28 international hospitality experts. Several different analysis techniques were applied to achieve the objectives. Firstly, the relationship between the intention to cancel or maintain the trip was analysed. The participants of the survey were distributed by several rules such as traveller's type, experience, probability of infection and the threat. The results of the study show that media coverage plays a crucial role in the relationship between risk perception and travel intention. During the pandemic, travel planning decisions are strongly influenced by confidence in communication from the local government about personal safety and security. Unofficial information regarding COVID-19 from social networks and confidence in the protection measures have a negative impact on the decision to go ahead with a travel plan. Experts also confirmed the importance of communication for tourists making travel decisions. They felt that clear information from public authorities was the key to reducing the risk of having no tourists.

3. Methodology

Figure 2 shows the process of the analysis. The research problem and the motivations of this thesis have been discussed in the previous chapters. Meanwhile, this chapter describes how the data has been collected, cleaned, and modelled. The last step of the work is to leverage a pre-trained sentiment analysis model for data analysis, which will be discussed in the next chapter.

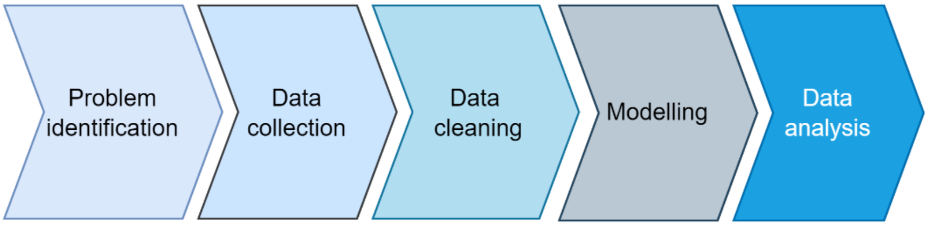

Figure 2. The process flow chart of the analysis.

3.1 Data Collection

In today's life, social media has become an essential part of our society, and people express their views and opinions by posting them on social media platforms like Twitter, Facebook, etc. Therefore, for our research, the potential data collection source is any of the social media platforms. Scraping data from Twitter for research is very popular, considering its worldwide reach and availability of different tools to access it in comparison to other platforms. Hence, we selected Twitter as our source of data collection.

Tweets in English were collected using Twitter API[2] with the help of Tweepy[3] to study the impact of COVID-19 on people's perception of travel safety. A list of keywords was needed for scraping specific tweets to collect the tweets that served our research purpose. Hence, before scraping the tweets using the API, travelling-related keywords were checked directly on the Twitter platform. Also, there are several online services which are available for analysing keywords. According to, Tripfore's[4] [29] analysis performed in 2020 shows that "safe to travel" has been used in several searches. Portland SEO Growth's website [5] shows several pairs of keywords that mention "insurance" and "restriction" [30] .

Based on the external search, keywords were selected to scrape the tweets for this thesis topic. As the thesis focuses on COVID's impact on travel, pandemic-related words such as "COVID", "coronavirus", and "virus" were added to some keywords. Taking into account the mindset of the people, we also considered the word "anxiety". Finally, the following keywords were selected: 'COVID travel', 'coronavirus travel', 'safe to travel', 'travel insurance', 'travel restriction', 'travel anxiety', 'travel again' and 'virus travel'.

Over 120k tweets were collected in total. However, Twitter is also considered a perfect platform for malicious accounts which use automated tweeting programs or spam accounts. Therefore, before cleaning the data, fake accounts had to be removed.

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[2] Tweet https://developer.twitter.com/en/docs/twitter-api

[3] https://www.tweepy.org/

[4] https://www.tripfore.com/most-popular-travel-keywords-world/

[5] https://www.portlandseogrowth.com/keywords-for/travel/

3.2 Detection of Fake Twitter Accounts

Whilst Similarweb[6] research shows that bots account for less than 5% of monetisable users, 21% to 29% of the monetisable content is derived from bots [31]. Considering that, a large amount of information on Twitter is likely biased and can strongly affect any research done on opinion mining.

In their article, Cresci et al. (2015) [32] analysed the features and rules proposed by Academia and Media for anomalous Twitter account detection. We followed some of the rules proposed by Cresci et al. (2015) [33] to detect and remove fake accounts in this work. Nevertheless, as the aim of this research is not to propose a model for detecting fake accounts, the metadata required to conduct this data cleansing was not acquired. For example, this work excludes metadata such as users with zero tweets or the source of the tweets. All tweets which were collected for our study have geo-location data.

Following Cresci et al. (2015) [32], this work used the following features to identify the suspicious accounts:

1) Friends / (followers^2) ratio,
2) Using the word "bot" in their username,
3) Using "bot" in their description,
4) Using default image,
5) Total tweets/retweets ratio,
6) Number of words in the user's name,
7) The user is not verified.

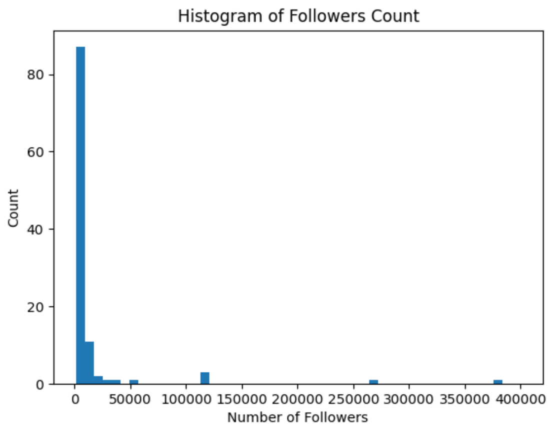

Figure 3. Histogram of users who have 0 friends but at least 1000 followers.

The research carried out by Cresci et al. (2015) [32] reported that friends / (followers^2) and bidirectional link ratio showed the best result for detecting anomalous Twitter accounts [4]. Because some users do not have followers, the result of the ratio is *inf*. One additional follower has been added to all users to avoid this issue. Some users showed anomalous behaviour as their friends / (followers^2) ratio was abnormally high. For regular users, the ratio is low as typically they have followers and at the same time, they follow others. For non-typical

[6] https://www.similarweb.com/blog/insights/social-media-news/twitter-bot-research-news/

accounts, the ratio is high as they do not have followers, but they follow a high number of users. People often buy fake followers to increase their popularity and social media presence. Moreover, a lot of fake followers are frequently automated bots. To cleanse the data of outliers accounts with a friends / (followers∧2) ratio over 100 have been removed.

Besides the high friends / (followers∧2) ratio, some accounts have zero following but a high number of followers. Figure. 2 demonstrates users who do not follow any account but have over 1000 followers. In the current dataset, 65 unique users do not follow anyone but have over 1000 followers. Since it is common for celebrities not to follow anyone, additional rules have been applied to find anomalous accounts amongst these 65 users: checking to see if the account is verified, and if it uses a profile picture. These are signs the account is actually legitimate.

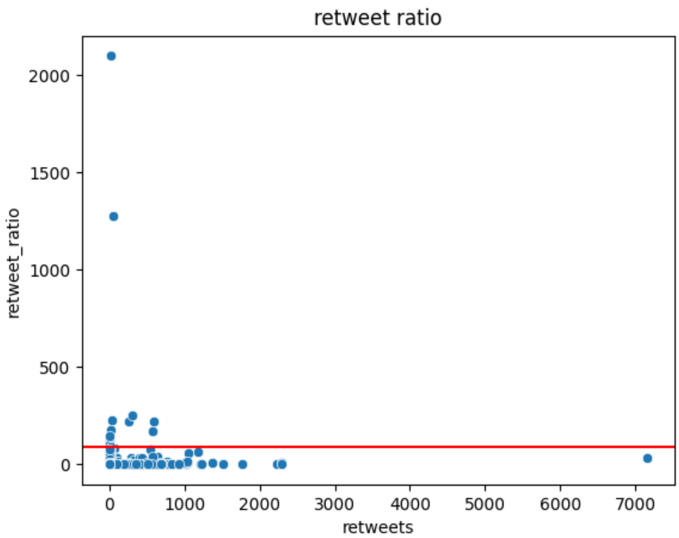

Figure 4. Retweet ratio where the red line marks 90% threshold.

Like in Cresci et al. (2015) [32] research, the threshold of the retweet ratio is 90 in this thesis, meaning that 90% of the tweets are retweets. Figure 3 shows only a few outliers. 13 unique users have a retweet ratio of over 90%. Because some of these 13 users have deficient retweets, another rule applies. In this work, potential spam or bot accounts have a retweet ratio of over 90% and over 50 retweets or retweet ratio of over 90%, and they created their account within the last six months.

In this dataset, no users had "bot" in their descriptions. However, two users had "Bot" in their name, indicating they were bots. Bots or spam accounts often have numbers in their name. Another name rule was created to remove these accounts: users with default images, numbers in their name, more than 500 tweets and no likes are most likely bots.

In conclusion, in this thesis, the following rules were:

1) Friends / (followers∧2) ratio over 100,
2) Friends / (followers∧2) ratio 0, and the user has at least 1000 followers, is not verified, and has a default image as a profile picture.
3) The retweet ratio is over 90%, and they have more than 50 retweets,
4) The retweet ratio is over 90%, and their account has been created in the last six months,
5) The user’s name has the word "Bot" at the end of their name ,
6) The user is not verified, has no friends, and follows one user (however, as mentioned above, to avoid calculation errors, one follower was applied to each user) and has more than ten tweets.

7) The user has the default image as their profile picture, the tweet has no likes, the user has more than 500 tweets, and their name includes numbers.

Table. 1 Results of the rule-based detection of fake accounts.

Category	Number of unique users	Number of tweets
Suspicious accounts (bots, spam, etc.)	82	117
Good accounts	83335	126942
Total	83442	127059

Table 1 shows the results after applying the above-written rules. The number of users detected as bots and spam accounts is small. Nevertheless, Similarweb's research [31] also revealed that Twitter has a relatively small percentage of bot accounts. The number of such accounts can also be affected slightly by the geo-location rule. Collected tweets had to have a geo-location ID.

3.3 Data cleaning

The data had to be cleaned to avoid noise and unwanted content from the collected tweets.

The following steps have been used for data cleaning in this work:

1) Removal of duplicate tweets,
2) Removal of URLs,
3) Removal of hashtags. Although hashtags are not removed each time for sentiment analysis, they can impact the results. This work aims to analyse general trends and overall sentiment about travel safety. However, hashtags can provide keyword and context analysis value, so they have been saved to separate columns.
4) Removal of special characters such as emojis and punctuation marks,
5) Removal of mentions,
6) Removal of stopwords.

After data cleaning, the dataset includes 80473 unique users and 116150 tweets.

3.4 Sentiment Analysis Task

In our thesis, we analysed the textual content of tweets leveraging a sentiment analysis (SA) model. Developing a SA model is not the scope of this thesis. Hence, we employed a pre-trained SA model that performed well on Twitter data. In this context, we employed TimeLM-21, a pre-trained SA model proposed by Loureiro *et al.* (2022) [34], that outperformed other models in the SA task on the TweetEval benchmark dataset.

In the recent past, Loureiro *et al.* (2022) [35] trained a model with around 124M tweets from January 2018 to December 2021 and finetuned it for sentiment analysis with the TweetEval benchmark. TweetEval is commonly used to evaluate the performance of the language models on Twitter data. It includes seven tweet classification tasks: emoji prediction, emoji recognition, hate speech detection, irony detection, offensive language detection, sentiment analysis and stance detection [34].

The base model is trained with data until 2019, starting from the original RoBERTa base and continuing with training the masked language model on Twitter data. The model was trained after every three months. Continuous training teaches models the current trends and helps them to be more accurate. For example, neither the original BERT nor RoBERTa are current with the COVID-19 pandemic, which is troublesome as most of the communication in recent years has been affected by this [34].

Figure 4 shows the results of various models based on the TweetEval benchmark. TimeLM-21 model has the highest score for sentiment classification.

	Emoji	**Emotion**	**Hate**	**Irony**	**Offensive**	**Sentiment**	**Stance**	**ALL**
SVM	29.3	64.7	36.7	61.7	52.3	62.9	67.3	53.5
FastText	25.8	65.2	50.6	63.1	73.4	62.9	65.4	58.1
BLSTM	24.7	66.0	52.6	62.8	71.7	58.3	59.4	56.5
RoBERTa-Base	30.8	76.6	44.9	55.2	78.7	72.0	70.9	61.3
TweetEval	31.6	79.8	55.5	62.5	81.6	72.9	72.6	65.2
BERTweet	33.4	79.3	56.4	**82.1**	79.5	73.4	71.2	67.9
TimeLM-19	33.4	**81.0**	**58.1**	48.0	**82.4**	73.2	70.7	63.8
TimeLM-21	**34.0**	80.2	55.1	64.5	82.2	**73.7**	**72.9**	66.2
Metric	M-F1	M-F1	M-F1	$F^{(i)}$	M-F1	M-Rec	AVG (F1)	TE

Figure 4. TweetEval test results of all comparison systems [34].

For performing SA tasks on our tweets, we used TimeLM-21 model that was updated in 2022 on the Hugging Face[7] website. In terms of average recall, the performance of the model on SA task is 73.7.

3.5 Using Artificial Intelligence Assistant

We used artificial intelligence tool Grammarly[8] for proofreading.

[7] https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest

[8] grammarly.com

4. Results

In this section, we present our findings on people's perception towards travel safety across different time spans of the COVID-19 pandemic. The COVID-19 pandemic is not yet over; hence we present our analysis by dividing the predefined data collection time period into four periods based on the severity of the pandemic. The predefined time period is divided into the following four time periods:

- Pre-COVID period,
- Pre-lockdown period,
- Lockdown period,
- Post-lockdown period.

In this work, the COVID-19 pandemic start date is considered January 30, 2020, when the World Health Organisation declared the outbreak a public health emergency of international concern [1]. Pre-COVID tweets were collected between January 1 2019, and January 29, 2020.

Lockdown periods were not the same in every country because of the severity of the death rate and the spreading of the virus. Hence, we could not define unique time periods for all countries. Our dataset consists of tweets from over 200 different countries. So, considering the required time and effort to analyse our study for all 200 countries individually, we redefine our dataset and divide the dataset into five parts: four countries and the rest of the world (ROW). The four countries include The United States of America, the United Kingdom, Canada, and India. Our selection criterion was governed by the percentage of tweets in the dataset of a country.

Table 2. Distribution of countries by the number of their tweets and their mean sentiment scores.

Country	Number of users	Number of tweets	Percentage of tweets	Positive	Negative	Neutral
USA	31460	43162	37.16%	0.13	0.20	0.66
UK	14955	22097	19.02%	0.14	0.18	0.68
Canada	4496	7869	6.77%	0.12	0.19	0.69
India	5471	7503	6.46%	0.10	0.16	0.74
ROW	24091	35519	30.58%	0.16	0.14	0.70

Table 2 shows the top four countries by their tweets' percentage and mean sentiment scores. Most tweets came from the United States. Because we collected tweets only in English, other European countries besides the UK did not stand out. One possible reason could be the use of native language while posting tweets. In our collected tweets, with respect to the number of tweets, the top four countries are those countries where English is widely spoken. It is essential to point out that some of these countries experienced several lockdowns due to numerous loss of lives; moreover, lockdowns were area specific. Even more, there were national and local lockdowns in the United Kingdom and India. For example, in the United States, the lockdown periods were state specific. In this thesis, the earliest lockdown date in each country is considered the beginning and the latest the end of the shutdown period

Table 2 shows that the majority of the tweets in our dataset are neutral. There are several reasons for the high number of neutral tweets:

1) textual content does not contain powerful negative or positive language,
2) textual content is written in complex language,
3) textual content includes sarcasm,
4) textual content is too short.

In order to understand the reasons why the majority of tweets were neutral, we manually checked some tweets and noticed that all the above-mentioned reasons were present. Some examples of the highly scored neutral tweets are: *"Lunch time after travel again", "Time to travel to Arrakis once again!", "Health protocol for travel to Indonesia for foreigners starting 12 January 2022.", "Testing times - could this COVID-19 health passport app could help revive travel and events?".* These examples show that neutral tweets are rather informative or do not include any strong emotion.

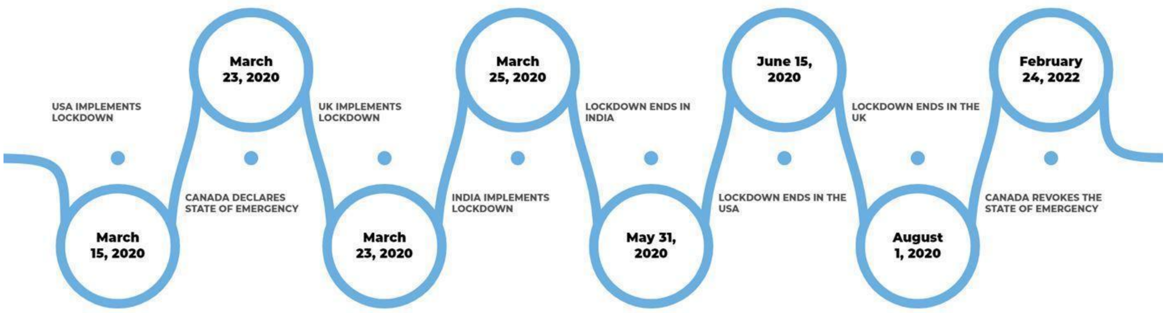

Figure 5. Timeline of COVID-19 lockdown periods in the top four countries.

Figure 5 demonstrates the timeline of COVID-19 lockdown periods in the top four countries. According to the Centers for Disease Control and Prevention (CDC)[9], the lockdown in the United States began on March 15, 2020 [36] and ended on June 15. The lockdown in the United Kingdom started on March 23, 2020 [37] , and ended on August 1, 2020 [38]. In India, the shutdown started on March 25, 2020 [39], and lasted until May 31, 2020 [40]. Canada declared a state of emergency on March 23, 2020 [41], until February 24, 2022 [42]. Considering this, the periods to analyse the trends have been divided as in Table 3.

[9] https://www.cdc.gov/

Table 3 Distribution of time periods by regions.

Region	Pre-COVID-19	Pre-lockdown	Lockdown	Post-lockdown
USA	01.01.2019-29.01.2020	30.01.2020-14.03.2020	15.03.2020-15.06.2020	16.06.2020-10.02.2023
UK	01.01.2019-29.01.2020	30.01.2020-22.03.2020	23.03.2020-01.08.2020	02.08.2020-10.02.2023
India	01.01.2019-29.01.2020	30.01.2020-24.03.2020	25.03.2020-31.05.2020	01.06.2020-10.02.2023
Canada	01.01.2019-29.01.2020	30.01.2020-22.03.2020	23.03.2020-24.02.2022	25.02.2022-10.02.2023
ROW	01.01.2019-29.01.2020	30.01.2020-14.03.2020	15.03.2020-15.06.2020	16.06.2020-10.02.2023

4.1 Exploring Trends and Patterns

This chapter focuses on analysing the trends and patterns of the four selected countries and the rest of the world (ROW). To understand the mindset of the people, we reviewed sentiment scores over time to find the trend. As shown in Table 2, most tweets were identified as neutral. Nevertheless, there is a visible pattern in each reviewed region.

Figure 6 shows the mean scores of the sentiments of the tweets over time in the United States, United Kingdom, India, Canada and the ROW. All graphs in Figure 6 show the same trend: more positive tweets than negative from quarter one of 2019 to the last quarter of 2019. Because of this, it seems that at the beginning of COVID-19, people were not scared of the pandemic. In the last quarter of 2019, negative tweets increased, which indicates an increase in fear among the people. During the pre-lockdown at the beginning of 2020, all regions experienced a peak of negative tweets. This is due to the fact that the first cases of COVID-19 in the respective regions were discovered at the beginning of 2020. The volume of news coverage related to COVID-19 peaked from late 2019 through the end of 2020, as compared to nowadays, when the topic is less covered. Due to the vaccination programmes across countries, the pandemic was under a bit of control in the last quarter of 2022. As a result, in the last quarter of 2022, positive tweets increased compared to negative tweets in the United Kingdom, the United States and India. In ROW the volume of positive tweets increased at the beginning of 2022. Canada experienced a state of emergency for a long time compared to other countries, as shown in Table 2; that might be why the volume of positive tweets stayed lower than negative tweets since the last quarter of 2019.

Given the uniformity of the observed pattern across different regions, it can be concluded that there has been a global impact of the COVID-19 pandemic to travel related tweets. Nevertheless, because most of the tweets were identified as neutral, the effect of the virus has not significantly impacted a person's negative perception. A word frequency analysis was conducted across various regions and periods, as detailed in the previous chapter, examining both positive and negative contexts separately and together to evaluate the impact of COVID-19 further.

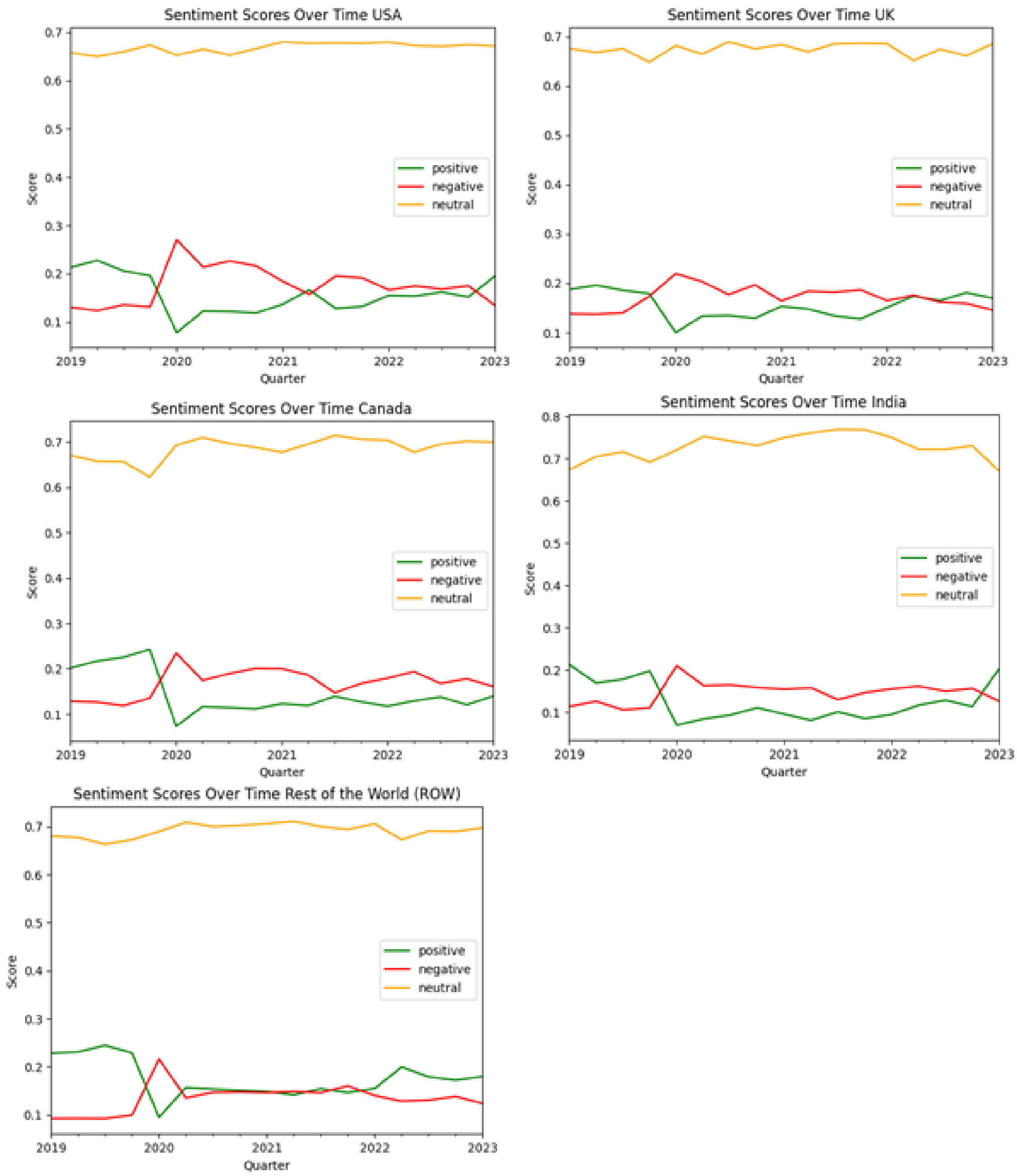

Figure 6. Mean sentiment scores over time.

4.1.1 Pre-COVID-19 Pandemic

Appendix 1 shows the number of tweets in different regions before COVID-19. We also included mean scores of varying polarity groups. It is essential to note that the pre-pandemic period's length was the same for all regions, as shown in Table 3. We divided tweets by their sentiment labels. Since the word frequency is viewed in positive and negative sentiment later in the research, it is essential to understand the size of the samples.

As the pandemic had not begun, Figure 6 shows that this period had the highest mean scores of positive tweets, as expected. The proportion of positive tweets was the largest in the ROW area, where 17.39% of the tweets were positive. The proportion of positive tweets was almost the same (~15%) for the USA, UK and India. Nevertheless, as Appendix 1 shows, the highest mean score of all positive tweets (0.79) belonged to Canada. Surprisingly the mean score of all pre-pandemic negative tweets was also highest in Canada (0.70).

We also conducted a word cloud[10] to evaluate COVID-19's impact on the tweets. Checking the frequency of the words during different periods can help to identify patterns and trends. Although a world cloud analysis is a good tool for understanding the frequency and detecting patterns, it does not include sentiment. Therefore, we also checked the frequency of the words from positive and negative tweets separately.

Figure 7 A word cloud of all sentiments during pre-COVID with sample sizes USA (5242 tweets), UK (2592 tweets), India (664 tweets), Canada (600 tweets) and others (5232 tweets).

[10] A word cloud is an image composed of the words in the text, where the size of each word varies depending on its frequency.

Figure 7 shows the word frequency of all sentiments before the pandemic. “Travel insurance” and “trip” have been frequently used in all regions. There was a similar trend in positive words such as “love”, “happy”, and “thank”; these words were mentioned in all regions before the beginning of the pandemic.

The sentiment of each tweet was obtained using the sentiment analysis model described in Section 3.3. In the data analysis, tweets having positive and negative sentiments capture people’s concerns. Since the positive and negative tweet buckets are significantly smaller, there are fewer tweets to analyse. Nevertheless, frequent words have been reviewed in the sentiment groups to understand people's emotions and feelings.

Figures 8 and Figure 9 demonstrate the word frequency of positive and negative sentiment during pre-pandemic. These words are often seen in word clouds as well. All regions indicate similar trends: frequently used words in negative tweets before the pandemics are “anxiety”, “travel”, “never”, and “insurance”. Although the volume of negative tweets was low in Canada, we can see that people were tweeting regarding “coronavirus” before WHO declared the virus outbreak a public health emergency of international concern. Considering external events, the first coronavirus case in Canada was on January 25, 2020 [41].

Because we did not exclude organisations, our dataset includes tweets regarding news and advertisements, often labelled neutral by the employed sentiment analysis model. As Figure 7 exhibited, “travel insurance” has been mentioned frequently in all sentiments. We reviewed some positive and negative tweets where it was mentieond to connect the text with emotion.

Some samples of positively labelled tweets from our dataset:

1) *“Literally, lucky I got travel insurance”* (Netherlands),
2) “*@ user Oh good rules there. Always be safe....and have your travel insurance policy in your phone, hahahah. Or sharpied on your arm is better.”* (USA)

Some samples of negatively labelled tweets from our dataset:

1) *“Brexit = massive increase in travel insurance costs for some disabled & ppl who are ill ! As ever, the billionaire Murdoch's Brexit coup will hurt the poorest”,*
2) *“I have the policy with Coverwise, It just doesn’t make sense to have a travel insurance policy that wouldn’t cover having to buy new tickets because the flight was cancelled?”*

Although “travel insurance” does not appear in Figure 9 for ROW and USA, people used it in positive tweets. In both positive examples, we can see a similar context; people were satisfied because they had insurance. Both samples of negative tweets are from the United Kingdom. It is visible that people did not complain about the concept of insurance but rather regarding price and product limitations.

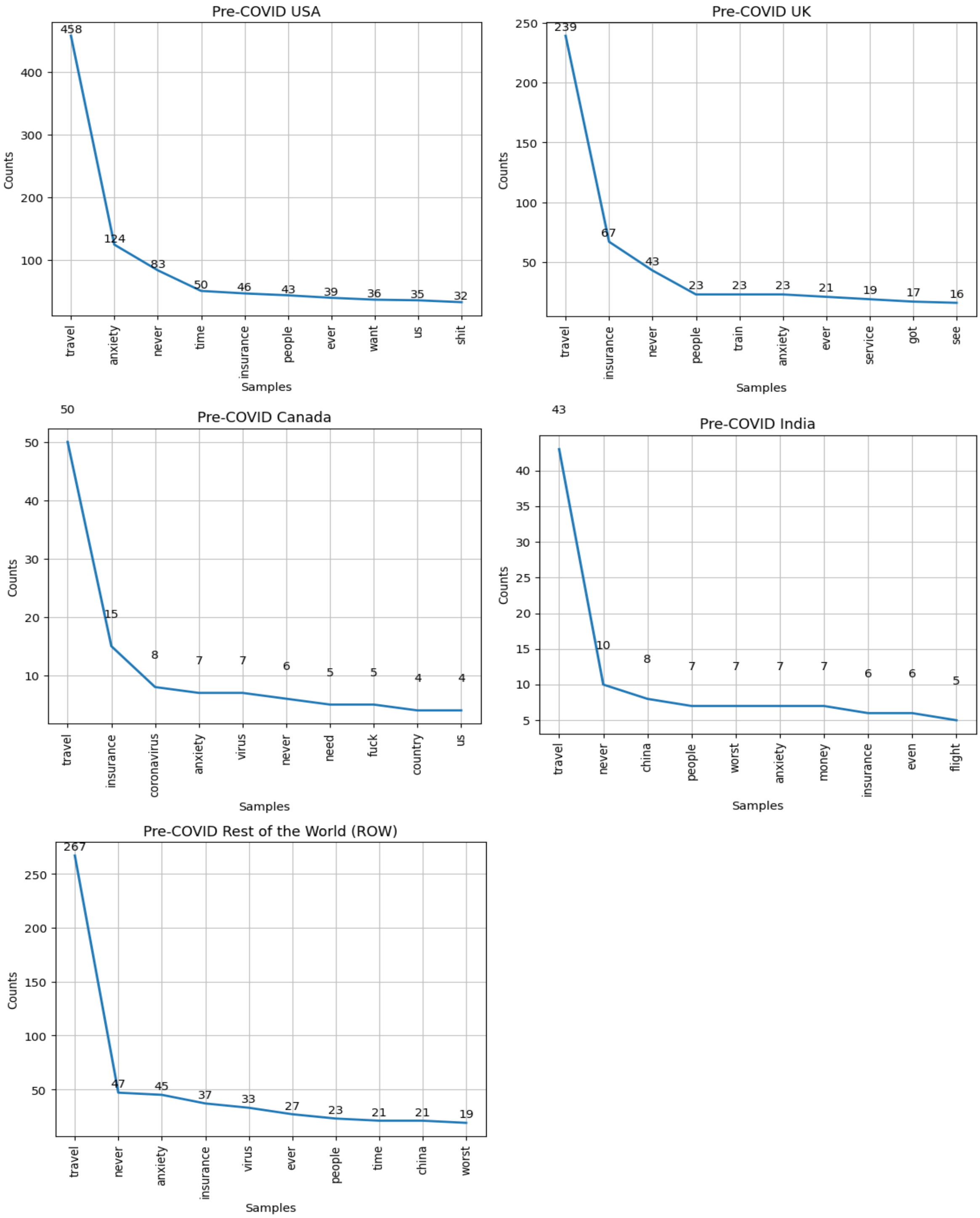

Figure 8. A word frequency before the COVID-19 pandemic of negative sentiment with sample sizes USA (490 tweets), UK (247 tweets), India (46 tweets), Canada (53 tweets) and ROW (282 tweets).

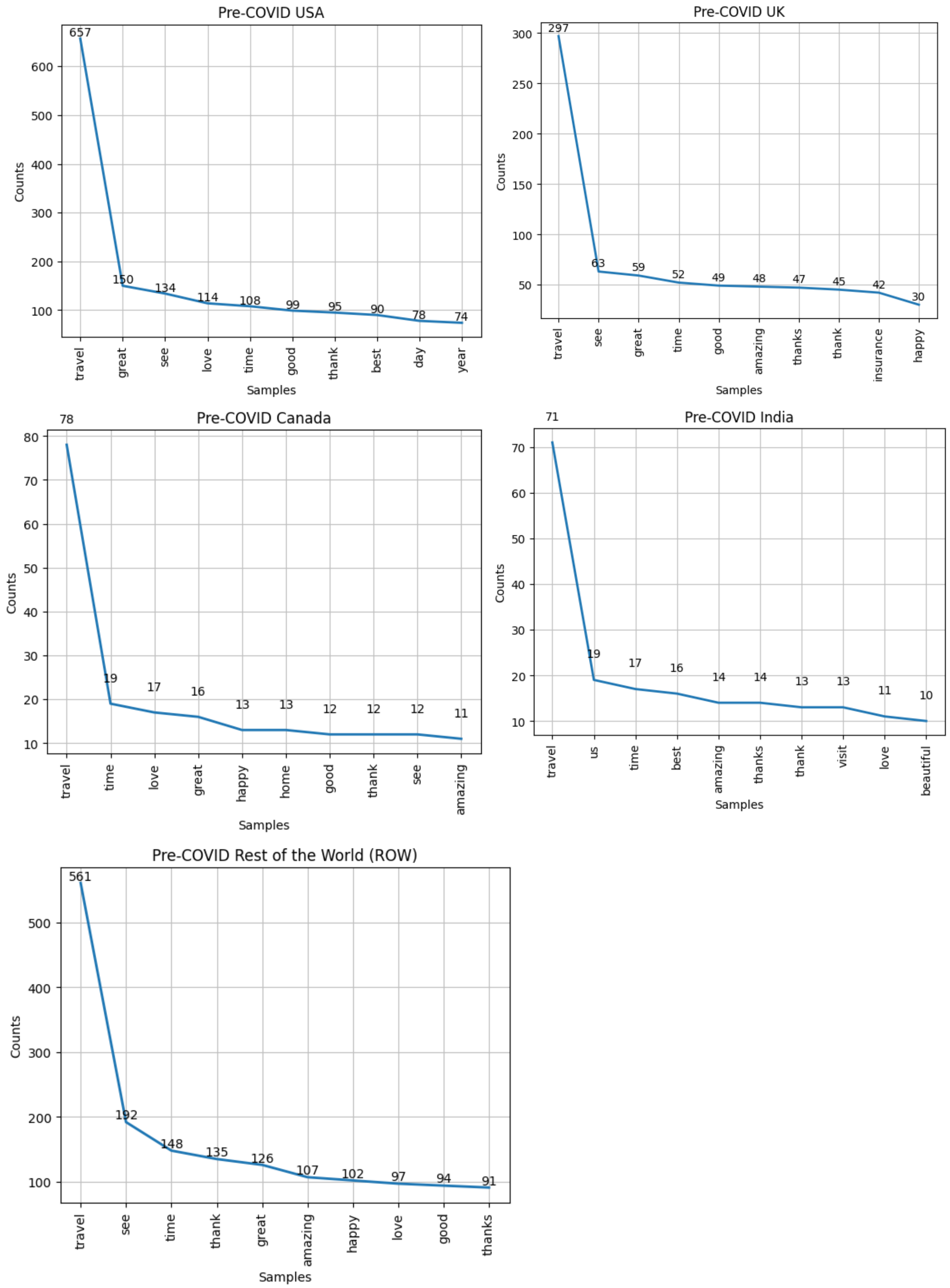

Figure 9. A word frequency before the COVID-19 pandemic of the positive segment with sample sizes USA (791 tweets), UK (342 tweets), India (90 tweets), Canada (94 tweets) and others (910 tweets).

4.1.2 Pre-lockdown

Pre-lockdown's length was different in each area. However, as Table 2 presents, the start date was the same for all regions, and the end date was either mid-March or the end of March. During the pre-lockdown period, the virus spread worldwide. Although governments had not imposed lockdowns yet, there were several restrictions. When the virus first appeared, several countries set initial limits on flights from China or required visitors from high-risk areas to quarantine [43]. Later the number of flights decreased even more.

Appendix 2 shows the sample sizes from pre-lockdown. Whilst the number of tweets decreased in the United States, the United Kingdom and other parts of the world, it increased in India and Canada. As the virus was spreading across the world, the number of tweets labelled negative increased in all regions. As a result, the negative tweets peaked in each region during pre-lockdown, as shown in Figure 6. The most significant change occurred in the United States: 23.09% of the pre-lockdown tweets were negative. Moreover, the mean sentiment score compared to other regions was also the highest (0.68). Due to the severity of the situation, India had the lowest number of positive tweets, only 1.81%. On the other hand, India had the highest mean score of positive tweets (0.78).

Figure 10. 10 A word cloud of all sentiments during pre-lockdown with sample sizes USA (4616 tweets), UK (2020 tweets), India (1047 tweets), Canada (869 tweets) and others (2918 tweets).

In Chapter 2, we have discussed three tendencies as possible changes in tourist behavioural patterns. One of the mentioned keywords was "cancellation" - more concerned travellers tend to cancel or postpone their trips due to potential health risks. Figure 10 shows that people from the United States, the United Kingdom and other parts of the world have tweeted regarding the cancellation. To understand the context, we reviewed several tweets; however, the majority did not indicate cancellation due to health concerns. Typically, there was involuntary cancellation by an accommodation provider or airline.

However, there were a few cases when individuals cancelled their trips voluntarily because of the coronavirus. For example, a tweet from Malaysia (ROW region in our dataset) in February 2020:

"Dear @User, if I would like to cancel my flights to Hanoi & Yunnan due to the recent Coronavirus outbreak, will the be any refund can be made? It is not safe to travel anywhere near China now □□□Pls help to confirm."

Furthermore, increasing numbers of tweets regarding health were coming from Canada.

Overall the majority of frequently used words were similar in all regions. Figure 11 demonstrates how keywords changed compared to pre-pandemic negative sentiment. Pre-lockdown's most commonly used words in negative sentiment were regarding the pandemic. We can see that people also started tweeting about the travel ban.

On sample from our dataset: *"We are canceling our honeymoon to Ireland that we were due to leave for in a week □ We booked it 8 months ago, and I'm devastated. Plus, our travel insurance doesn't cover anything because Ireland is not in lockdown/no hard travel ban from Aus Govt"* (Australia, tweet from March 13, 2020).

This sample demonstrates that individuals cancelled their holiday by themselves, however, not entirely voluntarily. Furthermore, the tweet highlights the lack of insurance functionality at the beginning of the crisis. Australia closed their borders to non-citizens on March 20, 2020, and advised citizens to return to Australia as soon as possible. Only essential travelling was allowed [44].

As shown in Appendix 2, the volume of positive tweets dropped rapidly. For example, in the USA, the pre-COVID positive tweets were ~15%; however, it drastically dropped to ~2.5% during the pre-lockdown period. Contrarily, the negative tweets jumped to ~23% during the pre-lockdown period, whereas it was ~9% before the pandemic. We observed the same pattern for the UK, India and ROW. Notably, for India, the positive tweets were only ~1.5% during this period. Figure 12 illustrates the frequency of positive tweets; no significant patterns exist. The words used are the same in each area.

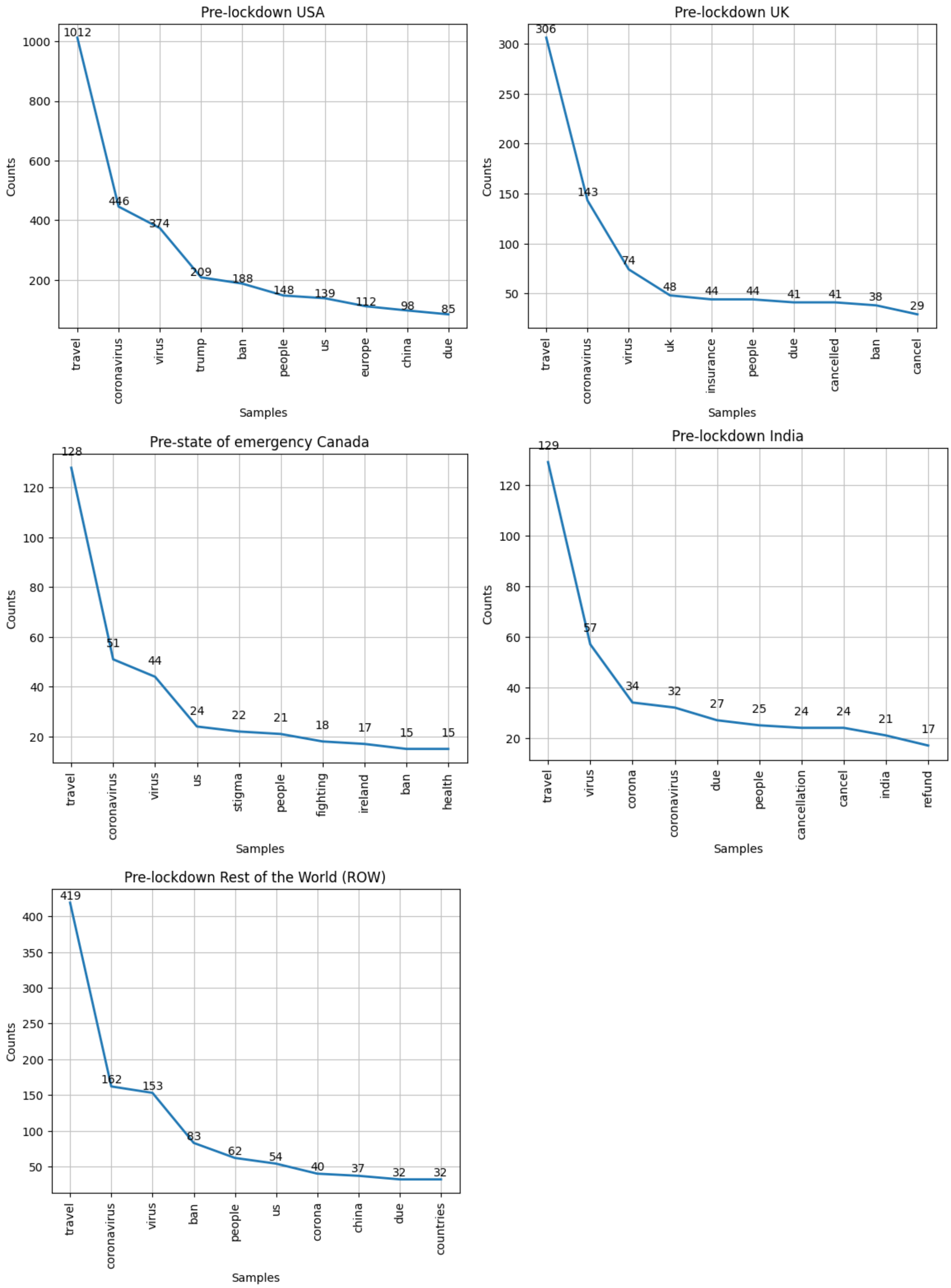

Figure 11. A word frequency before the lockdown of the negative segment with sample sizes USA (1066 tweets), UK (332 tweets), India (131 tweets), Canada (133 tweets) and others (437 tweets).

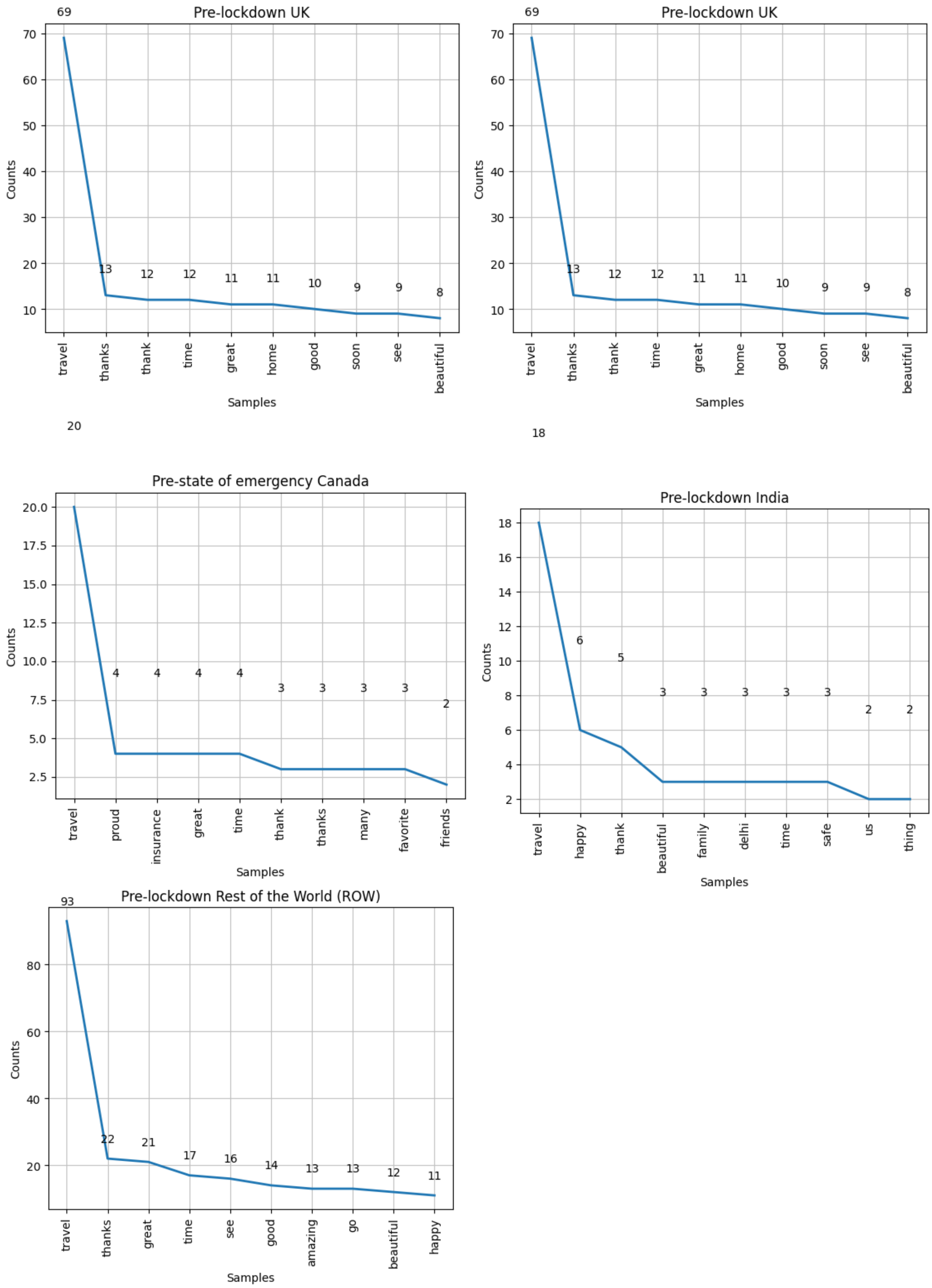

Figure 12. A word frequency before the lockdown of the positive segment with sample sizes USA (124 tweets), UK (85 tweets), India (19 tweets), Canada (21 tweets) and others (134 tweets).

4.1.3 Lockdown

Appendix 3 illustrates that the volume of tweets increased during lockdown. The possible reason could be as people were inside their home, and social media was the prime medium of their communication with others. As Table 3 showed, the shutdown periods varied by each country. We observed that the percentage of negative tweets dropped in all areas. This could be because lockdown reduced their risk of catching the life threatening COVID-19 virus, and they were therefore in a more positive mindset compared to the pre-lockdown period. The most significant portion of negative tweets still belong to the United States; 16.87% are negative. As Figure 3 shows, there is an increase in positive tweets in ROW. Furthermore, 8.14% of the tweets are positive and 9% negative. India had the most significant percentage of neutral tweets during the lockdown. 90.64% are labelled neutral. In addition, India had the least amount of tweets. The most positive tweets are from the United Kingdom, with a mean sentiment score of 0.73, and the most negative ones are from the United States, with a mean sentiment score of 0.65.

Figure 13 A word cloud of all sentiments during lockdown with sample sizes USA (8108 tweets), UK (4715 tweets), India (1495 tweets), Canada (5580 tweets) and others (6778 tweets).

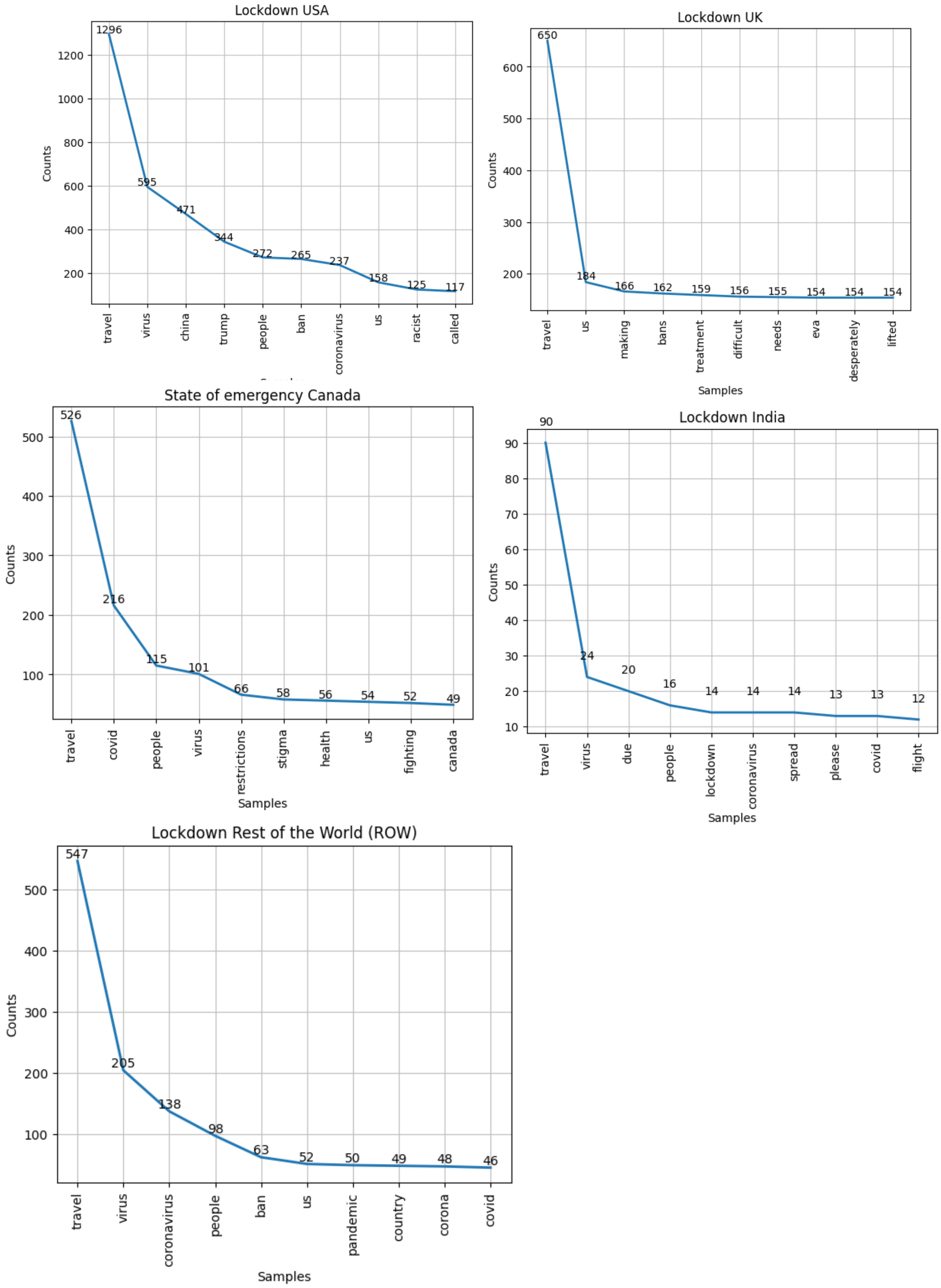

Figure 14. A word frequency before the lockdown of the negative segment with sample sizes USA (1368 tweets), UK (674 tweets), India (95 tweets), Canada (552 tweets) and others (610 tweets).

During the lockdown period, the general topics of the tweets were similar worldwide. Nevertheless, from words such as “desperately need”, “treatment”, and “need treatment”, we can see a discernible trend towards heightened concern over health risks. The state of emergency lasted around three years in Canada. Therefore, it is expected that people were tired. Although “fighting stigma” was mentioned during the pre-lockdown period, the frequency of using it had increased. Canada also experienced several protests regarding COVID-19 vaccine mandates and restrictions, such as the Freedom Convoy [45]. We investigated the keyword “fighting stigma” and noticed that the majority came from one user, a Canadian non-profit organisation sharing the news. Most of their shared posts during the state of emergency in Canada were COVID-19 related. Surprisingly, people did not tweet much regarding protests. Words such as “convoy”, “protest”, and “freedom convoy” were not frequently used during the state of emergency.

Figure 14 illustrates the frequency of the words in the negative sentiment tweets. The number of tweets regarding COVID-19 decreased compared to the previous period. Nevertheless, the volume of negative tweets increased in most regions. The data highlights that most content in each area was identical except for the United Kingdom. Rather than the virus itself, people tweeted regarding the treatment of it or fear of getting it. Some samples from this period regarding “treatment” are:

1) “*I’d love to go to Spain. Unfortunately, I can’t get Travel Insurance for Covid. The risk of getting it and then having to pay for hospital treatment is too high*.”
2) *“@user Had you acted sooner, as other countries with low numbers of Covid deaths did, we would not be in this predicament. It should have started with airports being closed to non essential travel and testing, isolating, treatment being continued.”.*
3) *“Pls can you RT for little Eva..♥ She is 9 and desperately needs treatment in the US once travel bans are lifted.. COVID-19 is making fundraising difficult but we can’t give up”.*

These three samples demonstrate the three different contexts of tweeting about “treatment”. Whilst the first individual wants to travel but is afraid of the costs, the other supports the travel restrictions but is pessimistic about how COVID-19 is handled at the government level. The third person represents a group who needed medical care for other illnesses but could not get it due to COVID-19.

Compared to the previous periods, the context of positive tweets has changed. Figure 15 illustrates that “safe” is among the most frequently used words from all regions except for India. We searched for some samples from the dataset to study the context of using “safe” in tweets.

1) *“Enjoy your next holiday from your living room - never need to travel again. Virtual is just fine and it is safe.” (Tweet from Canada)*
2) *“Remind me about African penguins and a beautiful beach. I don’t mind going there again when it’s safe enough to travel” (tweet from South Africa)*
3) *“I can’t wait to travel when it is safe again! Our Africa trip is postponed this summer so I will enjoy Botswana... Botswana themed wallpaper that is!! This beauty was installed just in time for our clients to enjoy…”(tweet from the United States).*

These tweets show that people wanted to travel. However, they were concerned about safety.

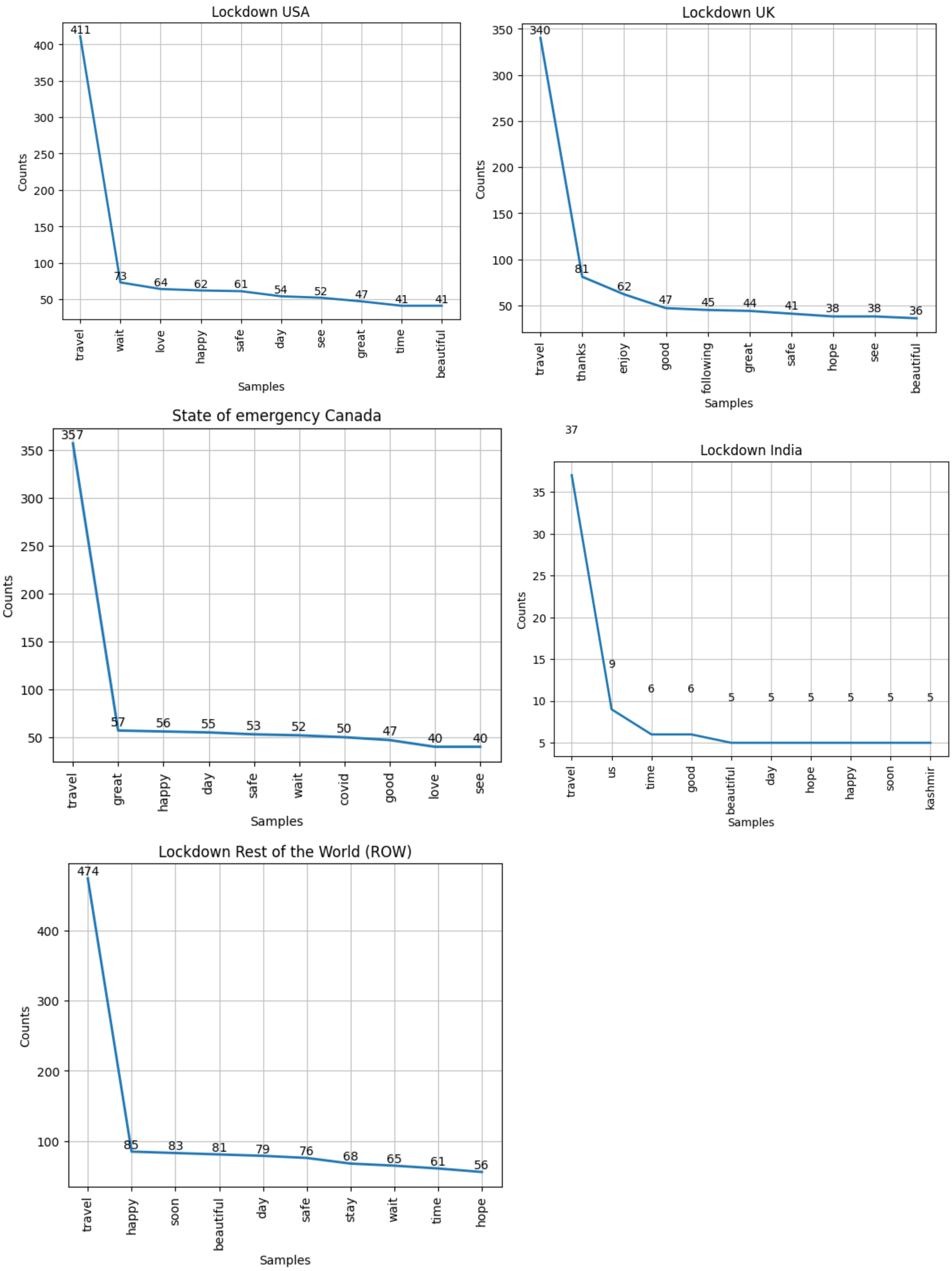

Figure 15. A word frequency before the lockdown of the positive segment with sample sizes USA (473 tweets), UK (409 tweets), India (45 tweets), Canada (385 tweets) and others (552 tweets).

4.1.4 Post-lockdown

Compared to the previous periods, the volume of the tweets was the maximum during the post-lockdown period; the possible reasons could be that in most of the regions this was the longest period and health risks had reduced due to vaccination. Appendix 4 demonstrates the distribution of the tweets at that time. There are more positive tweets than negative in ROW. Moreover, the difference between positive and negative tweets decreases in all the regions, as highlighted by Figure 6. The mean sentiment scores of positive tweets were the highest in the United Kingdom and ROW, 0.77. Furthermore, the mean sentiment scores of the negative tweets were the highest in the United Kingdom and the United States, 0.67.

Figure 16. A word cloud of all sentiments during post-lockdown with sample sizes USA (25196 tweets), UK (12770 tweets), India (4297 tweets), Canada (820 tweets) and others (20591 tweets).

Figure 16 illustrates the most frequently used words during this period. “Travel restriction” and “Travel ban” were still discussed; nevertheless, they are less significant in the word cloud than in the previous period.

Figures 17 and 18 show the most frequent words used in the negative sentiment tweets during post-lockdown. Although frequent words in the negative tweets are similar to the previous periods, the terms in positive tweets have changed. Surprisingly, “covid”, which has been either used in neutral or negative tweets, became positive.

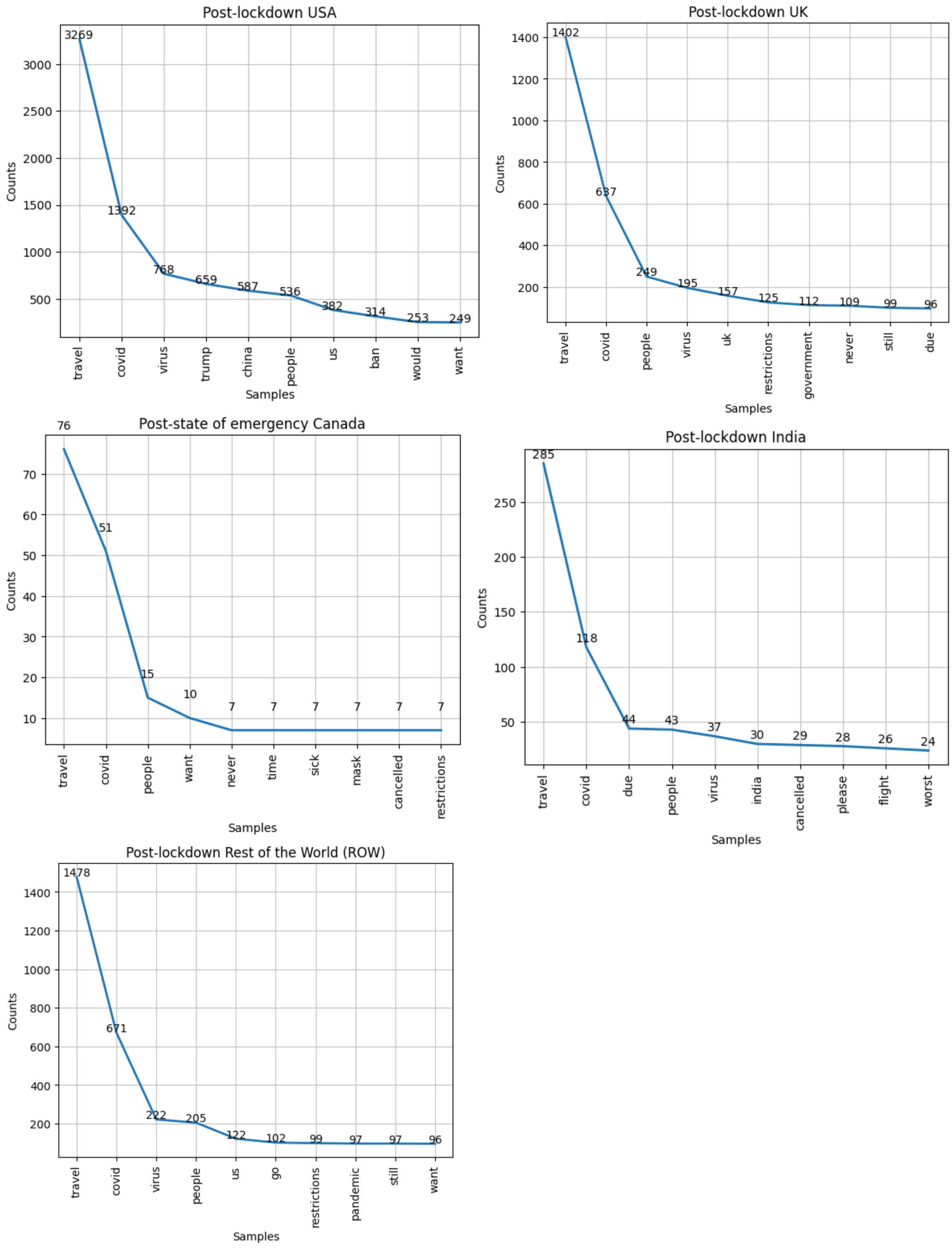

Figure 17. A word frequency before the lockdown of the negative segment with sample sizes USA (3472 tweets), UK (1469 tweets), India (291 tweets), Canada (84 tweets) and others (1604 tweets).

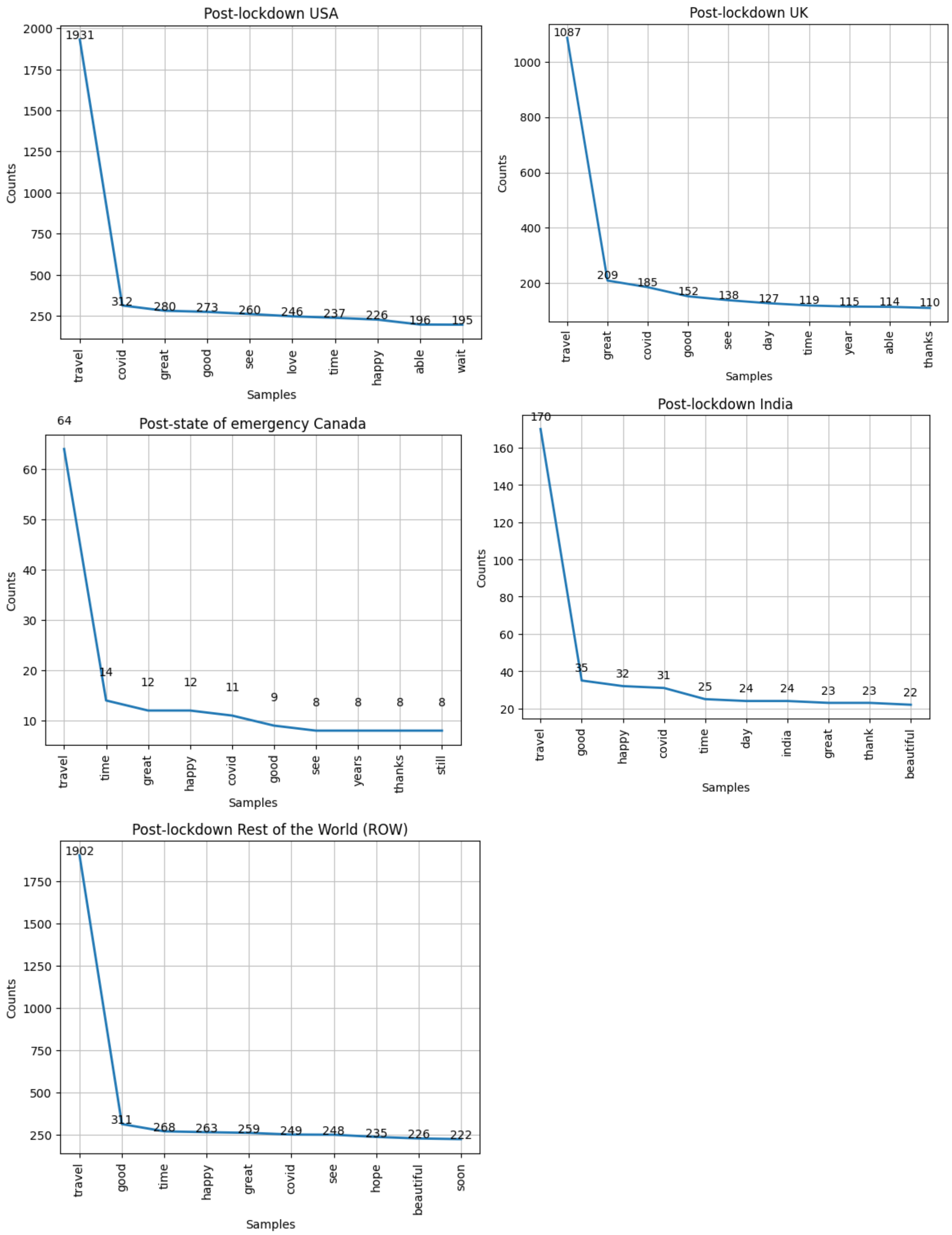

Figure 18. A word frequency before the lockdown of the positive segment with sample sizes USA (2124 tweets), UK (1211 tweets), India (203 tweets), Canada (71 tweets) and others (2191 tweets).

To highlight the context, we manually checked positively labelled tweets:

1) *“Good to see @user offering excellent travel insurance including Covid cover now that the international travel ban has lifted and "DO NOT TRAVEL" advice has been amended. Can now go away confidently feeling protected. (Note - not if you have a cruise as part of your trip)”*
2) *“Covid test be4 my flight back to US was positive. glad I had a gr8 travel insurance that covered extra time I spent in Zurich Finally back home after 2 negative tests! Don’t underestimate infection probabilities when attending large gatherings!”*

These two samples exhibit tweets which were positive and mentioned “COVID”. Nevertheless, the context of the tweets exhibits that people are satisfied and feel secure because of travel insurance.

5. Conclusion

The COVID-19 pandemic not only cost human lives but also harmed industries like tourism. As safety concerns are a primary factor in tourists' willingness to travel, the tourism industry can be adversely affected by crises or disasters. Compared to 2019, the coronavirus caused a 72% decline in international tourist arrivals in 2020 and 71% in 2021 [10]. It represents a 2.1 billion USD loss in international arrivals in both years combined. This thesis aimed to study how COVID-19 impacted on the public's perception of travel safety.

Here, we summarize our findings by answering the two research questions which are formed at the beginning of the work to study the topic.

RQ1. What factors influence travel risk perception during the COVID-19 pandemic?

During pre-lockdown, people started to tweet more about cancellations of their travel plans. There were involuntary cancellations by airlines, accommodation or tour providers as well as voluntary cancellations due to the increased concerns regarding safety and health risks. Concerns regarding safety increased even more during lockdown when people started to tweet more regarding being safe which were identified as positive tweets, as shown in Figure 15. Furthermore, in the UK, people tweeted regarding "treatment" in negative tweets. These tweets also included safety and health concerns. Overall, the following changes in the behaviour were noticed:

1) People postponed their trips because of their concerns over safety and health risks,
2) People postponed their trips because there was no suitable insurance or they were unaware of such insurance that covered COVID-19 medical expenses,
3) People did not intend to travel at all because it was too risky in terms of their lives and financial ability.

In conclusion, the most significant factors influencing travel risk were virus, lack of safety and health risks.

RQ2. How does COVID-19 affect peoples' views of "travel insurance"?

Usually, the insurance aims to provide protection against risks. Hence, people take travel insurances to cover scenarios such as flight cancellation, medical illness during travel, etc. As shown in Figure 7, "Travel insurance" was discussed already before the COVID-19 pandemic. Individuals cancelled or postponed their trips because travel insurance was not fulfilling their safety need. Nevertheless, during COVID-19 it added an extra level of security to people. Even more during the post–lockdown, travel insurance made people more comfortable about their travel plans. To sum up, at the beginning of the pandemic, the insurance did not cover people's expectations; therefore, there was frustration due to its lack of utility. However, as the pandemic progressed, people felt more satisfied with the travel insurance.

At the beginning of the work, the hypothesis: "People's perception of travel safety has decreased due to COVID-19, and they are re-evaluating their travel motivations due to the current risks" was proposed. Data showed a tendency to cancel and postpone trips due to safety concerns during pre-lockdown and lockdown periods. People had the most negative feelings during pre-lockdown. On the other hand, during other periods, the majority showed neutral feelings regarding the virus. As Figure 6 showed, since the middle of 2022, people started to show more positive feelings.

5.1 Limitation and Future Work

Although some changes were detected in the behavioural pattern during COVID-19, most tweets had neutral polarity. Therefore, it is difficult to link the emotion with the text. In addition, the posts of companies and organisations were not excluded from the dataset; therefore, the dataset included news and advertisements.

This thesis employed an already pre-trained model for the sentiment analysis task. Based on the literature, the model performed well on Twitter data. However, fine-tuning it was not possible because, in that case, a subset of collected data had to be manually annotated, which was rigorous and time-consuming. It might have affected the performance of the employed model, and some tweets might not be correctly analysed. Another limitation of this work could be considering the tweets which were posted in English only. Hence, this study could have been more accurate if the tweets in other languages would be considered too. However, analysing all the countries and different languages could be very challenging to process within the time scope of this Master's thesis.

As part of the future work, to obtain more accurate results the limitation of this thesis needed to be addressed:

- Besides English, non-English tweets would be included, in particular some European languages. Also, more countries across the globe would be added to the dataset.
- In order to leverage fine-tuning on the employed pre-trained sentiment analysis model, a subset of tweets for fine-tuning the model would be manually annotated.
- In addition, measures to separate tweets of organisations from private individuals would be taken.

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7. Appendices

I. Distribution of Tweets During Pre-COVID-19 and Their Mean Sentiment Scores

Country	No of tweets	Label	% of the tweets	Positive	Neutral	Negative
USA	791	Positive	15.09%	0.77	0.22	0.01
	490	Negative	9.35%	0.02	0.31	0.67
	3961	Neutral	75.56%	0.12	0.79	0.10
UK	342	Positive	13.22%	0.78	0.21	0.01
	242	Negative	9.35%	0.02	0.29	0.69
	2003	Neutral	77.43%	0.10	0.79	0.10
India	90	Positive	13.55%	0.76	0.23	0.01
	46	Negative	6.93%	0.02	0.30	0.68
	528	Neutral	79.52%	0.10	0.81	0.09
Canada	94	Positive	15.67%	0.79	0.20	0.01
	53	Negative	8.83%	0.02	0.28	0.70
	453	Neutral	75.50%	0.10	0.79	0.10
ROW	910	Positive	17.39%	0.78	0.21	0.01
	282	Negative	5.39%	0.02	0.30	0.68
	4040	Neutral	77.22%	0.11	0.81	0.08

II. Distribution of Tweets During Pre-lockdown and Their Mean Sentiment Scores

Country	No of tweets	Label	% of the tweets	Positive	Neutral	Negative
USA	124	Positive	2.69%	0.75	0.24	0.01
	1066	Negative	23.09%	0.02	0.30	0.68
	3426	Neutral	74.22%	0.06	0.76	0.18
UK	85	Positive	4.21%	0.77	0.22	0.01
	332	Negative	16.44%	0.02	0.31	0.67
	1603	Neutral	79.36%	0.07	0.78	0.15
India	19	Positive	1.81%	0.78	0.21	0.01
	131	Negative	12.51%	0.02	0.34	0.65
	897	Neutral	85.67%	0.06	0.78	0.16
Canada	21	Positive	2.42%	0.73	0.26	0.01
	133	Negative	15.30%	0.02	0.33	0.65
	715	Neutral	82.28%	0.06	0.77	0.17
ROW	134	Positive	4.59%	0.75	0.24	0.01
	437	Negative	14.98%	0.02	0.33	0.65
	2347	Neutral	80.43%	0.06	0.78	0.16

III. Distribution of Tweets During the Lockdown and Their Mean Sentiment Scores

Country	No of tweets	Label	% of the tweets	Positive	Neutral	Negative
USA	473	Positive	5.83%	0.75	0.23	0.01
	1368	Negative	16.87%	0.02	0.31	0.67
	6267	Neutral	77.29%	0.08	0.78	0.14
UK	409	Positive	8.67%	0.76	0.23	0.01
	674	Negative	14.29%	0.02	0.33	0.65
	3632	Neutral	77.03%	0.08	0.79	0.13
India	45	Positive	3.01%	0.74	0.24	0.01
	95	Negative	6.35%	0.02	0.34	0.65
	1355	Neutral	90.64%	0.06	0.80	0.14
Canada	385	Positive	6.90%	0.77	0.22	0.01
	552	Negative	9.89%	0.02	0.33	0.65
	4643	Neutral	83.21%	0.08	0.78	0.14
ROW	552	Positive	8.14%	0.75	0.23	0.01
	610	Negative	9.00%	0.02	0.33	0.65
	5616	Neutral	82.86%	0.08	0.79	0.12

IV. Distribution of Tweets During Post-lockdown and Their Mean Sentiment Scores

Country	No of tweets	Label	% of the tweets	Positive	Neutral	Negative
USA	2124	Positive	8.43%	0.76	0.23	0.01
	3472	Negative	13.78%	0.02	0.31	0.67
	19600	Neutral	77.79%	0.09	0.78	0.13
UK	1211	Positive	9.48%	0.77	0.22	0.01
	1469	Negative	11.50%	0.02	0.31	0.67
	10090	Neutral	79.01%	0.09	0.79	0.13
India	203	Positive	4.72%	0.74	0.25	0.01
	291	Negative	6.77%	0.02	0.34	0.64
	3803	Neutral	88.50%	0.07	0.81	0.12
Canada	71	Positive	8.66%	0.74	0.25	0.01
	84	Negative	10.24%	0.02	0.32	0.66
	665	Neutral	81.10%	0.08	0.78	0.13
ROW	2191	Positive	10.64%	0.77	0.22	0.01
	1604	Negative	7.79%	0.02	0.33	0.65
	16796	Neutral	81.57%	0.09	0.80	0.11

V. Access to the Code

Source code available here: https://github.com/aaltmets/Masterthesis and via QR code from Figure 19.

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Figure 19. QR code of the source code

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