Understanding Discussions around COVID-19 and Vaccination Hesitancy in Canada

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Introduction

When the COVID-19 virus arrived in Canada in March of 2020 and cases of community transmission were confirmed, all of Canada's provinces and territories declared a state of emergency. Distinct measures, to varying degrees, have been taken by all provinces and territories in an effort to control the spread of the virus (Rosenberg, Syed, and Rezaie 2020).

The extensive usage of social media–a public platform where individuals produce, share, and exchange ideas, opinions and information–accelerates the spreading of information, misinformation, and opinions about public events and health crises (Rosenberg, Syed, and Rezaie 2020).

Using Twitter, a popular social media platform and a key data source in many infodemiology studies, we aim to outline the salient topics discussed around COVID-19, the primary concern and the relative engagement of each topic, and the public's response to the pandemic and vaccination measures, including vaccine hesitancy.

This study uses tweets sampled from within Canada over a span of three non-consecutive days to examine and gain a better understanding of the discussions occurring around COVID-19 in Canada. A thousand tweets were manually annotated for topic and sentiment, after which point an analysis of sentiment by topic, engagement of each topic, and top 10 words by term frequency-inverse document frequency (tf-idf) were performed.

We found that Canadians had an overall negative view towards vaccine related topics such as efficacy, mandates and Canadian government handling. Furthermore, Canadian twitter users are still very concerned with statistics about COVID-19 cases, deaths, rehabilitation and appeared to have a slightly more positive attitude about child vaccination. We will discuss in further details these findings.

Data

Our data set is a collection of 1000 English COVID-19 related tweets geo-located in Canada. We collected 1000 tweets published on Monday the 22^{nd}, Wednesday the 24^{th} and Friday the 26^{th} of November 2021. From these 3000 tweets, we sampled 333 from each day using the `random.sample()` function and one last random tweet from a randomly selected file. When collecting 1000 tweets for each day, we randomly sampled 10 keywords from a list of 30 COVID-19 related keywords[1] that we created. With these 10 keywords, we used the `str.join()` function to build a query string where all words were separated by '*OR*'. The query string of COVID-19-related keywords was passed to the Twitter API with parameters specifying language, '*en*', for tweets in English, and the desired creation date of the tweets. From all tweets in the API response, the following criteria were used to select tweets for each batch of 1000:

- The tweet had a defined location: either the tweet's country was set to Canada or the user's location contained the name of one of Canada's provinces, territories or "Canada".
- The tweet's text was unique: each tweet's text was hashed and compared to all other hashes from all previous tweets.

For tweets that satisfied both conditions, we only kept the following features we thought useful for the analysis: *id, text, date of creation, url, location* and whether it was a *retweet*. We also created the following columns in the CSV to be filled in the annotation phase: *topic* and *sentiment*. In the tweet's text body, new lines were replaced by tab characters.

Methods

Data Collection and Sampling

Twitter API To perform the data collection, we used `Tweepy`, an open-source Python library that provides an interface of the Twitter API. With Twitter API's Elevated Access developer account and the endpoint `api.search_tweets`, we were able to collect tweets that satisfied the following:

- Tweet language was English.
- Tweet text contained a keyword (case-insensitive).
- Tweet creation date was specified date.

[1]moderna, spikevax, pfizer, biontech, pfizer-biontech, astrazeneca, janssen, johnson&johnson, j&j, covid, covid19, covid-19, covid2019, covid-2019, sars-cov-2, coronavirus, vaccination, vaccinations, vaccine, vaccines, antivaccine, anti-vaccine, antivax, anti-vax, antivaxxer, anti-vaxxer, antivaxxers, anti-vaxxers, mRNA

Location Filtering Initially, we attempted filtering tweets by Canadian provinces, territories and their respective capitals but we encountered a number of mismatches such as Victoria, Australia instead of Victoria, BC. Therefore, we decided to simply look for provinces, territories names and distinctive city names[2] or ”Canada”.

Text Uniqueness In order to ensure uniqueness in the tweet’s text content such that the same tweet or retweet does not to appear more than once in our data set, we hashed each tweet’s text and compared all new tweets’ hashed text with the hashes previously collected. Originally, we tried hashing the tweet’s id, but retweets have the same id as the original tweet. Hashing the text directly bypasses this problem and therefore ensures complete uniqueness of tweets’ content.

Collection Days We chose to collect 1000 tweets from non-consecutive days–Monday, Wednesday and Friday–in the hopes of obtaining a more diverse, wide-ranging and representative data set. The large number of daily collected tweets would also provide a broader data set when sampling a third of each respective day for the final collection. New measures and mandates are updated often, therefore collecting tweets across a broader time span is a better representative of varied discussions surrounding COVID-19.

Keyword Selection In an attempt to collect varied, representative data, we decided to create our own list of keywords[1] related to COVID-19. The first keywords selected were variations of ”COVID-19”, such as ”coronavirus” or ”covid2019”. We chose to exclude keywords that are considered politically incorrect, like ”Wuhan virus” or ”China virus” since we felt that the inclusion of these negatively-charged terms was counterproductive to understanding the overall sentiment and discussions around COVID-19.

Also included were keywords related to vaccination (”vaccinations”, ”antivax”, etc.). Within these two categories, variations accounted for the inclusion or exclusion of hyphens, such as in the keyword ”covid-19”: both ”covid-19” and ”covid19” were included in the keywords. Vaccine names and their corresponding brand names (ex. ”moderna” and ”spikevax”) were also included. Since this study concerns discussions related to COVID-19 in Canada, we used only those vaccines approved by Health Canada (Canada 2020).

Building the Typology The open-coding process allowed us to devise seven different topics to describe the data. We defined the first topic as ”vaccine discussion”, which includes all vaccine-related discussion except ”child vaccination”, including but not limited to subtopics such as vaccine effectiveness, opinions about getting vaccinated, and vaccine passports. The second topic is ”child vaccination”, tweets categorized under this topic do not refer to the discussion about vaccines in general, but rather about how and where children can get vaccinated, how vaccines can protect children, and some attitudes about vaccination of children. Many tweets contained strong, subjective opinions about pandemic related rules and mandates such as wearing masks, so we defined this topic as ”mandate opinion”. The ”mandate opinion” topic also includes discussion of mandatory vaccination for employment, such as in a hospital. The fourth topic is ”political opinion”, which also refers to subjective expression but within a specific range of politically relevant issues such as international vaccine distribution and pandemic policy disagreements across governments, health organisations, and political parties. Furthermore, the topic ”COVID impact” reflects how the pandemic effected people travelling, gathering, quality of life, life experiences, and mental health effects. The ”information” topic refers to the number of COVID cases, deaths, rehabilitation, and news about the pandemic from around world. Lastly, we define the topic ”other”, which includes miscellaneous topics such as conspiracy theories or misidentified tweets that to not fit accurately within the boundaries of the previously defined topics.

Retrieved Features We retrieved the features *id, text, date of creation, URL, location* and whether it was a *retweet* from the extended tweet information. We also introduced the features *topic* and *sentiment* as empty columns. These columns were filled in later during the data annotation and were critical for the data analysis. The *retweet* status and *topic* distribution were used to perform engagement analysis. The *text* feature was used for sentiment, topic annotation and Term Frequency–Inverse Document Frequency (tf-idf) analysis. The *URL* feature was used during manual annotation in cases where the *text* had multiple symbols or was a response to other tweets, therefore difficult to understand on its own. Finally, from tweet text content, we replaced newlines with tabs for readability.

Data Annotation and Analysis

Initially, we conducted an open coding of 20% (200) of the final tweets. This helped us build the typology–define the topics–that would be used to categorize all tweets collected. Once the typology was built, we did human coding of 1000 tweets, including the ones that were previously open-coded (re-coded to fit new topics). During this process, tweets were also annotated for a *positive*, *negative*, or *neutral* sentiment. With all annotated tweets, we were able to do 3 different kinds of analysis: sentiment, engagement and Term Frequency–Inverse Document Frequency (tf-idf).

Sentiment Contents of the *information* topic often showed news, practical matters, objective description or announcements, it was natural to label a grand majority of them as *neutral*. Tweets which are labeled as *positive* sentiment, normally showed initiative, encouragement and positive life experiences. Negative sentiment was relatively hard to identify. Posts that had obvious symbols of direct accusation, calling out, complaints were classified as *negative*. Expressing personal negative feelings such as anxiety, angry, dreadfulness and bewildering is also a part of *negative* sentiment. We acknowledge that irony and some enigmatic proverbs were

[2]Ottawa, Alberta, Edmonton, British Columbia, Vancouver, Manitoba, New Brunswick, Fredericton, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec, Saskatchewan, Regina, Northwest Territories, Nunavut, Iqaluit, Yukon

not easy to identify and since the annotator(s) had to label tweets' sentiment combining context and background, the sentiment is subjective and may mismatch the initial aim of the author.

Once tweets' sentiment was annotated, we analyzed sentiment by counting the amount of tweets coded positive, negative and neutral per topic respectively (see Figure 1).

Engagement Two methods were used to perform engagement analysis on the collected tweets; one method analyzed engagement with our defined topics across the whole data set, the second method aimed to determine engagement with tweets within each topic.

To analyze overall engagement by topic, the percentage of tweets coded as one of the seven topics (see section* 4.1) out of the total 1000 tweets was calculated for each category. Overall engagement is critical to understanding the spread of data across our defined categories.

To determine engagement within each topic, tweets that were retweeted–therefore, shared–were calculated as a percentage of the total tweets within a topic. In this way, the values are normalized across each topic and can therefore be compared accurately.

Term Frequency–Inverse Document Frequency (tf-idf) To gain a better understanding of what is being discussed within the topics and validate our topic definitions, term frequency-inverse document frequency (tf-idf) was performed. The tf-idf metric evaluates the importance of a word to a document in a collection; the importance of a word increases relative to the number of appearances of the word in the document, which is offset by the overall frequency of the word in the collection.

The tf-idf analysis processes the tweet's text content and therefore requires it be appropriately cleaned. First, all text was converted to lower-case so that stop-words could be consistently recognized and removed as well as ensuring, for example, that the tf-idf value of "covid" would be the same as "CoViD".

To remove stop-words from the tweet content, we combined our keywords[1] and the list of English language stop-words provided by `text.ENGLISH_STOP_WORDS` from the Python `string` library. The decision to include our keywords[1] as stop-words was prompted by our first attempt at a tf-idf analysis, which included many of the keywords[1] within the top 10 words by tf-idf value, which is consistent with the logic that at least one keyword is guaranteed to appear in each tweet. Therefore, removing the keywords allows us to better understand the vocabulary being used to discus these topics.

Punctuation was also removed from the text using the Python `string` library, which provides a complete list of punctuation as `string.punctuation`. Our first pass at tf-idf analysis replaced punctuation with spaces, but we found that resulted in the inclusion of many separated prefixes or words that were otherwise not constructive in building a better understanding of discussions of COVID-19 in Canada.

After the text was cleaned, the tf-idf analysis was performed on our data set, in which a "document" is one of defined topics and the "collection" is the entirety of the data set (1000 annotated tweets). The tf-idf for each word was calculated by counting the number of appearances (term frequency, *tf*) for each unique word in a topic and the inverse document frequency for each word by `math.log(documents/usages)`, where *documents* is the number of topics and *usages* is the number of topics that a given word appears in. The term frequency and inverse document frequency for a given word were multiplied together to get its tf-idf value.

Results

Topics

The topics selected were:

- Vaccine discussion (*vd*)
- Mandate opinion (*om*)
- Political opinion (*op*)
- Information (*i*)
- COVID impact (*ci*)
- Child vaccination (*cv*)
- Other (*o*)

Topic Sentiment Analysis of the *positive*, *negative*, and *neutral* sentiment of each topic revealed that discussions around vaccines, child vaccinations, information, and "other" were primarily *neutral*, whilst the remaining topics (COVID impact, mandate opinions, and political opinions) expressed primarily *negative* sentiments; none of the topics had a primarily *positive* sentiment.

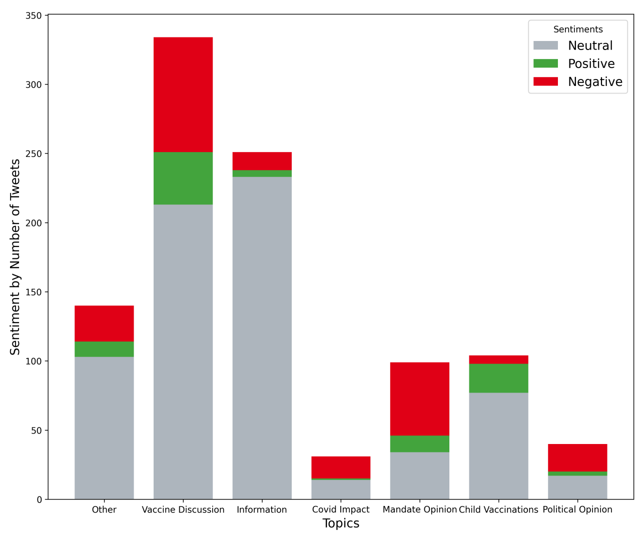

Figure 1: Positive, negative, and neutral sentiment of topics surrounding the discussion of COVID-19 in Canada.

In "vaccine discussion", 64% of tweets were *neutral* and only 11% of tweets had a *positive* sentiment. 74% of tweets in the "child vaccination" topic were *neutral* and 20% were *positive*. Tweets regarding COVID-19 information and news were the most *neutral*; 93% of tweets in the topic were labelled *neutral*. The sentiment towards the impact of COVID-19 on daily life was 52% *negative*, "mandate opinion" was 54% *negative*, and "political opinion" was 50% *negative*. Excluding the 140 tweets categorized as "other", 68% of tweets across all topics were categorized as *neutral*, 22% were labelled as *negative*, and the remaining 10% were *positive*.

Topic Engagement We performed two different analysis for topic engagement, first(Figure 2) across all topics, secondly(Figure 3), among each topic.

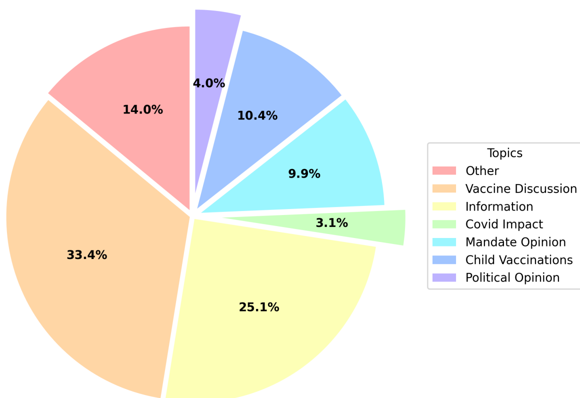

Figure 2: Percent engagement of tweets by count for topics surrounding the discussion of COVID-19 in Canada.

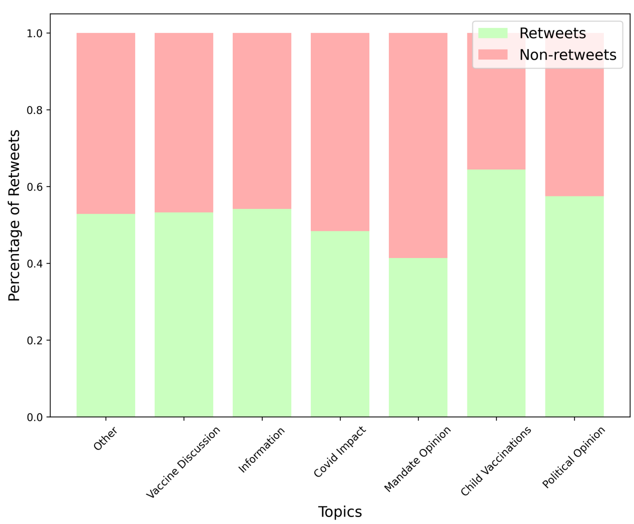

Figure 3: Engagement of tweets by percent retweeted for topics surrounding the discussion of COVID-19 in Canada.

Engagement with topics related to COVID-19 in Canada varied greatly across our defined topics. As evidenced by Figure 2, 58.5% of tweets collected fell under two topics: "vaccine discussion" and "information". Tweets labelled as "other" accounted for 14.0% of the data collected, and the remaining four categories were spread across 27.4% of the data. Tweets related to the impact of COVID-19 made up the smallest proportion of tweets collected at 3.1%.

Considering an alternate metric for engagement, we can examine the percentage of tweets that were retweeted per topic, as seen in Figure 3. In contrast to the engagement analysis performed across the defined topics, retweet analysis within each topic showed that roughly 50% of tweets were retweeted in each category. A maximum of 64% tweets were retweeted in the "child vaccinations" category; a minimum of 41% of tweets were retweeted in the "mandate opinion" category.

Term Frequency–Inverse Document Frequency

The top 10 words with the highest term frequency-inverse document frequency for each topic, ordered by percentage engagement over all topics, are outlined in Figure 4.

Topic	Top 10 Words by tf-idf value, in descending order.
Vaccine Discussion	think, protection, rates, shit, booster, dont, rape, inequity, select, promote
Information	active, deaths, reports, central, outbreaks, reported, identified, nov, rates, positive
Other	aaron, county, rodgers, tweet, revenue, assistance, concern, parliament, updates, times
Child Vaccinations	kids, aged, eligible, appointment, parents, children, booked, appointments, guardians, tuesday
Mandate Opinion	rid, war, think, visitors, warming, huts, witch, exist, wanna, silent
Political Impact	chinas, democrats, migrants, ltc, percent, worst, lpc, msm, employment, rise
COVID Impact	restrictions, enacts, worried, awake, kourtpenner, marks, southern, laid, basic, lockdowns

Figure 4: Top 10 words in each topic by tf-idf value, in descending order.

Discussion

Interpreted Results

We found that the main salient topics discussed around COVID-19 were

- Vaccine discussion in general (efficacy, mandates and opinion), accounting for 33.4% of the collected tweets.
- COVID-19 related information (statistics and news), accounting for 25.1% of the collected tweets.
- Other (unrelated to vaccines/mandates/information relevant to our discussion), accounting for 14.0% of the collected tweets.
- Child vaccinations (information, discussion and opinion), accounting for 10.4% of the collected tweets.

These four topics account for 82.9% of the data set.

The primary concerns of the *vaccine discussion* topic were questioning/discussing the protection vaccines bring, booster shots and the inequality of vaccine access. We found that this topic had a high relative engagement, since it had a high frequency of occurrence–over a third of the tweets collected are accounted in this topic– suggesting that Canadians have a strong desire to express their opinions. The *vaccine discussion* topic's sentiment was overall neutral, over half of tweets were considered neutral but the negative sentiment annotated tweets count is at least double of positive sentiment annotated tweets. This insight suggests that there is a larger amount of people that disagree on government handling of the pandemic and vaccination efficacy.

The primary concerns of the *COVID-19 information* topic were statistics about active cases, deaths related to the virus and new possible outbreaks. Its relative engagement was significant–around a quarter of the tweets collected– and a large portion of these tweets (slightly more than 50%) were retweets, therefore simple share of information. More than 90% of the tweets from this topic had a neutral sentiment. Nonetheless, from the remaining tweets, negative sentiment annotated tweets were again at least double the positive sentiment annotated tweets. From this, we can observe that Canadians are still preoccupied with figures concerning COVID-19 and possible new outbreaks that might disrupt our current situation. Canadians seem to still express a larger amount of negative opinions concerning COVID-19 information.

The primary concern of the *Other* topic was Aaron Rodger's controversy and US news. It's not surprising that Canadians are interested in United States' handling of the pandemic and celebrities' attitude about the vaccine.

Finally, the primary concerns of the *Child vaccination* topic were the eligibility of children to get vaccinated and where to take appointments. The relative engagement of this topic was fairly high–around 10% of all tweets collected– since it was during the time it had been announced children were eligible. Over 60% of the tweets in this topic were retweets and while neutral sentiment still accounted for over 60% of the tweets, this is the only topic where the positive sentiment annotated tweets had a higher proportion than negative sentiment annotated tweets. This exhibits Canadians have a positive attitude towards child vaccination.

Overall, the public's response to the pandemic and vaccination measures, including vaccine hesitancy is more negative than positive in the Twitter platform. Canadians still seem concerned, doubtful and pessimistic of vaccine efficacy and government measures.

Limitations

We believe some characteristics of our approach and decisions taken along the execution of this study limited it's results. First, we had a very small sample that was not representative enough to be able to have a statistically stable image of the Canadian's discussions' salient topics and overall attitude about the pandemic. Our sample happened in the time child vaccination became available in Canada and the new African variant Omicron came to be, therefore has a significant place in our study, while this has not been the case for most of the time of the pandemic. Second, understanding the sentimental, emotional responses evoked by COVID-19, especially within the confines of specific topics, is a difficult and inherently subjective task. It requires that those involved in the annotation process suppress their own preconceived notions and opinions about sensitive and emotive topics. Therefore, we acknowledge that there is a strong possibility of unconscious bias that was introduced during the manual sentiment annotation process. Third, the selection of tweets based by province, territory or distinctive city leaves out many regions uncovered and therefore our results are skewed towards opinions in cities. Fourth, the random sampling of keywords– to make up a query string to collect tweets– could be flawed if most of the keywords are selected from the same topic, just different variations (e.g all ways to write COVID-19). Finally, we hashed the tweet's text to ensure uniqueness but if it was a retweet with one added word, it will have a completely different hash and have repeated information. These are the main limitations we thought about among many other more that could yield more detailed results.

- for sentiment: engagement is not evenly spread (ci, om, op very negative, but make up a small % of the data)

Group Member Contributions

- Nathalie Redick: Responsible for
  - Report writing (methods, results).
  - Data collection (researched and assembled a list of keywords, tweet text hashing for uniqueness).
  - Data analysis (graphs, tf-idf, engagement and sentiment analysis).
- Gabriela Rueda: Responsible for
  - Report writing (introduction, data, methods, discussion).
  - Data collection (tweet retrieval with API, location filtering)
  - Open coding of 200 tweets used to define topics.
- Yusen Tang: Responsible for
  - Annotated final data set for topic and sentiment.

References

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