

Investigating the Impacts of Policy Stringency on the Public Perceptions of Pandemic Policies, Sentiment
Analysis of Tweets During the Second and Third COVID-19 Pandemic Waves in Ontario

by

Bailey Marie Grigg

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Statement of Contributions

Bailey Grigg was the sole author of Chapters 1, 2, and 5. The data pre-processing and data analysis methods described in Chapters 3 and 4 were created in collaboration with Dr. Jasleen Kaur. Dr. Jasleen contributed by providing the Python pipeline code used to prepare the datasets and complete the initial zero-shot classification and sentiment analyses. This code also created the initial graphs used for trend analysis.

Abstract

Background: Public sentiment plays a critical role in shaping compliance and trust during public health crises. The COVID-19 pandemic was the first example of an infodemic, and the significant amount of social media data from that time period can be useful for understanding public responses and experiences throughout the pandemic. This study explores emotional responses to COVID-19 policy interventions in Ontario, Canada, using Twitter data to assess how public sentiments varied across lockdowns, mask policies, and vaccine mandates. The research aims to understand how policy stringency and a regional context influenced public attitudes throughout the pandemic.

Methods: Data from the Twitter API was collected and analysed. Tweets posted between December 1st, 2020 and June 30th, 2021 from app users in Ontario were compiled and sorted using zero-shot classification into subgroups for relevant categories – vaccine mandates, mask policies, and lockdown measures. These tweets were then analyzed using sentiment analysis and the COVID-19 Stringency Index to identify trends in the sentiments expressed on Twitter over time, considering changes in the strictness of various pandemic measures.

Results: Initial temporal analysis identified key events that led to notable sentiment changes, such as sentiment spikes following the announcement of the CERB program in March, followed by lockdown sentiments declining sharply in April after the use of the “provincial emergency brake”. Lockdown sentiments remained consistently neutral to negative, with no significant threshold effects or time-based recovery. Vaccine mandates showed a positive shift in sentiment beyond identified stringency breakpoints, with further improvement over time. Mask mandates initially received positive sentiments but declined sharply after passing a stringency threshold. Ottawa Twitter users expressed more positive and emotionally reactive sentiment than Toronto users, particularly in response to lockdown and vaccine policies.

Conclusion: Social media data offers valuable insight into public sentiment dynamics during health emergencies. Findings suggest that policy framing and perceived intrusiveness significantly influence emotional responses, with vaccine mandates benefiting from proactive messaging and civic framing. Regional differences underscore the importance of localized communication strategies. These results can inform future public health interventions by emphasizing the role of timing, tone, and threshold sensitivity in shaping public trust and engagement.

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Table of Contents

Author’s Declaration	ii
Statement of Contributions.....	iii
Abstract	iv
Acknowledgements	v
List of Figures	ix
List of Tables.....	x
List of Abbreviations.....	xi
Chapter 1: Introduction	1
1.1 Background	1
1.1.1 The COVID-19 Pandemic and Ontario’s Second Wave	1
1.1.2 Social Media and the COVID-19 Infodemic	2
1.2 Literature Review	4
1.2.1 Introduction to Social Media Research	4
1.2.2 Social Media Data	4
1.2.3 Methods for Social Media Analysis	5
1.2.4 Uses and Areas of Research	6
1.2.5 Impacts of Misinformation	7
1.2.6 Influential Accounts	7
1.2.7 Outcome Monitoring	8
1.2.8 Relevance and Gaps in Current Literature	10
Chapter 2: Research Questions.....	12
2.1 Trends and Changes in Public Sentiment Scores	12
2.2 Investigate Contextual Factors and Policy Stringency	12

2.3	Compare Sentiment Scores for Public Health Interventions By Location	12
Chapter 3: Methods		13
3.1	Study Design	13
3.2	Description of Datasets and Sample.....	13
3.3	CIHI COVID-19 Interventions Dataset.....	15
3.4	COVID-19 Stringency Index.....	15
3.5	Zero-Shot Classification.....	16
3.6	Sentiment Analysis.....	17
3.7	Manual Validation.....	18
3.8	Summary Statistics Dataset for Analysis.....	18
3.9	Summary and Visual Analysis	19
3.10	Statistical Analysis	20
Chapter 4: Results		22
4.1	Objective 1: Sentiment Trends Over Time.....	24
4.2	Objective 2: Regression Analysis.....	25
4.2.1	Lockdowns	25
4.2.2	Vaccine Mandates	27
4.2.3	Mask Policies.....	30
4.3	Objective 3: City-Level Analysis	32
4.3.1	Lockdowns	32
4.3.2	Vaccine Mandates	34
4.3.3	Mask Policies.....	36
Chapter 5: Discussion.....		40
5.1	Lockdowns	40

5.2	Vaccine Mandates	42
5.3	Mask Policies	43
5.4	City-Level Analysis.....	45
5.5	Lockdowns	46
5.6	Vaccine Mandates	46
5.7	Mask Policies	47
5.8	Summary	47
5.9	Limitations and Mitigation Strategies	48
5.10	Significance.....	49
	References	51
	Appendix A Summary of Results.....	62
	Appendix B Stringency Index Coding Scheme.....	65
	Appendix C Manual Validation.....	67
	Appendix D Legend of Events Overlay for Figure 4	68
	Appendix E Monthly 3-Day Rolling Averages	69
	Appendix F Code Repository	70

List of Figures

Figure 1.	Page 19	Data processing flowchart
Figure 2.	Page 23	Graph of Monthly Tweet Volume (three relevant policy themes)
Figure 3.	Page 23	Average Monthly Sentiment Per Theme Line Graph
Figure 4.	Page 24	Graph of 7-day Rolling Sentiments with Events Overlay
Figure 5.	Page 26	Piecewise Regression Models for Lockdown-related Tweets
Figure 6.	Page 29	Piecewise Regression Models for Vaccine Mandate-related Tweets
Figure 7.	Page 31	Piecewise Regression Models for Mask Policy-related Tweets
Figure 8.	Page 38	Average Sentiment Score Per Theme by City
Figure 9.	Page 39	3-Day Rolling Sentiment Trends by City

List of Tables

Table 1.	Page 14	Twitter dataset parameters, remaining tweet data after data pre-processing.
Table 2.	Page 22	Summary of data processing results
Table 3.	Page 26	Lockdowns Piecewise Regression
Table 4.	Page 27	Ridge Regression: Lockdowns
Table 5.	Page 28	Vaccines Mandates Piecewise Regression
Table 6.	Page 30	Ridge Regression: Vaccine Mandates
Table 7.	Page 31	Piecewise Regression Mask Policies
Table 8.	Page 32	Ridge Regression: Mask Policies
Table 9.	Page 33	Piecewise Regression Lockdowns by City
Table 10.	Page 34	Pieced Ridge Regression Lockdowns by City
Table 11.	Page 35	Piecewise Regression Vaccine Mandates by City
Table 12.	Page 36	Pieced Ridge Regression Vaccine Mandates by City
Table 13.	Page 37	Piecewise Regression Mask Policies by City
Table 14.	Page 38	Pieced Ridge Regression Mask Policies by City

List of Abbreviations

AIC	Akaike Information Criteria
API	Application Programming Interface
CERB	Canadian Emergency Relief Benefit
ML	Machine Learning
MSE	Mean Squared Error
NLTK	Natural Language Toolkit
PPE	Personal Protective Equipment
SARS-CoV-2	Severe acute respiratory syndrome coronavirus 2
VADER	Valence Aware Dictionary for Sentiment Reasoning
WHO	World Health Organization

Chapter 1: Introduction

1.1 Background

1.1.1 The COVID-19 Pandemic and Ontario's Second Wave

On the 11th of March 2020, a viral disease pandemic was declared by the World Health Organization (WHO) in response to the rapid global spread of the novel coronavirus, SARS-CoV-2 (Infection Prevention and Control Canada [IPAC], 2023). Soon after its emergence in China in November 2019, the virus rapidly spread to almost 200 countries by March 2020, and travel restrictions, public closures, and social distancing measures were quickly implemented around the world to slow the spread of the infection (IPAC, 2023).

The highly contagious respiratory virus is commonly spread through droplets or airborne particles. When an infected individual sneezes, coughs, or speaks, it causes infectious aerosol particles to travel through the air to be inhaled by any individuals the infected party is near (World Health Organization [WHO], 2021). COVID-19, the illness caused by the SARS-CoV-2 virus, is typically mild to moderate in severity; however, infection can still lead to severe illness, especially in those with underlying medical conditions and older adults (Public Health Agency of Canada [PHAC], 2022). COVID-19 has also been shown to cause “Post COVID-19 Condition” or “Long COVID”, where the symptoms of COVID-19 persist for longer than 12 weeks after infection (Public Health Agency of Canada [PHAC], 2024). Symptoms can vary in severity, disappear and reappear, and may occur regardless of the seriousness of an individual's initial COVID illness (PHAC, 2024). This condition presents differently between cases, with many possible symptoms, and can cause serious physical and mental health challenges, as well as long-term disability (PHAC, 2024).

The pandemic's spread generally followed a series of waves, a pattern characterized by a surge of new cases followed by a decrease in case count trends (Johns Hopkins Medicine & Maragakis, 2022). In Ontario, seven of these waves were reported between

February 2020 and November 2022 (Public Health Ontario [PHO], 2023). The first three being defined by the following dates, Wave 1 - February 26, 2020 to August 31, 2020 (188 days), Wave 2 - September 1, 2020 to February 28, 2021 (181 days) and Wave 3 – March 1, 2021 to July 31, 2021 (153 days) (PHO, 2023, Wu et al., 2021). The second wave of the pandemic proved to be much more severe than the first, with cases of COVID-19 drastically increasing from September 2020 into January 2021, peaking at 3945 new cases and a seven-day rolling average of 3,545.7 on January 10, 2021 (CBC News, n.d.). At the height of the second wave, Ontario reported 24,875 active cases in the week of January 3, 2021 (Public Health Ontario [PHO], n.d.). Along with record-high daily new-case reports, the second wave of the pandemic also saw the coronavirus death toll surpass 5000 people, and the deadliest outbreak in the province since the start of the pandemic. December 2020 marked the commencement of Ontario's vaccination rollout plan, administering the first vaccines to priority populations like healthcare workers and seniors (Nielsen, 2021). By December 21, intensive care unit (ICU) occupancy in hospitals for COVID-19 was 20 times higher than at the beginning of September (Office of the Premier, 2020c). By the end of the second wave, the province surpassed 7,000 cumulative deaths from COVID-19 by March 3, 2021, and 303,763 cumulative cases (Nielsen, 2021, Public Health Ontario [PHO], 2021). The third wave was even more severe, with new cases peaking at 4,812 on April 16th and a 7-day average of 4,292, setting a record for the number of new cases in a 24-hour period (CBC News, n.d.). Through the third wave, Ontarians saw delays in the vaccine rollout, continued strains on the long-term care and hospital systems, and the COVID-19 death toll surpassed 8,000 deaths by the end of April (CBC News, n.d.).

1.1.2 Social Media and the COVID-19 Infodemic

COVID-19 was unique among previous pandemics as it was the first instance of a pandemic in the digital age (Schulz et al., 2023). Given the lockdowns and rise in remote work and activities throughout the pandemic, social media and digital technologies were key channels for information dissemination, and for many, were the main method for maintaining social relationships (Bilodeau et al., 2021). Through the pandemic, Canadians exhibited increased

internet use, leveraging the internet for video conferencing with loved ones, streaming video content, shopping for physical goods and groceries, and working or studying from home (Bilodeau et al., 2021).

Along with the social and practical benefits of digital infrastructure during the pandemic, like spreading information, encouraging social connectedness, and maintaining productivity, high social media use also contributed to the occurrence of an “infodemic”, a term referring to an overabundance of information both on and offline during a disease outbreak (World Health Organization [WHO], 2020a). In an infodemic, the overload of information can make it difficult for the public to parse through the mass amount of content to find the information they are looking for (WHO, 2020a). An infodemic will also include a mix of accurate and inaccurate information, regardless of whether the intent of sharing it is to purposely deceive the public to advance an agenda or not (WHO, 2020a). The spread of this false information can have serious negative repercussions; this content can undermine public health campaigns, increase stigmatization, and reduce adherence to public health guidelines (WHO, 2020a). Ultimately, the mental and physical health of the public may suffer as a result (WHO, 2020). As seen throughout the COVID-19 pandemic, misinformation led to highly polarizing debates surrounding COVID-19, a lack of trust in the government, vaccine hesitancy, and a distrust in vaccine science (WHO, 2020 a). Over time, these issues led to increases in hate speech and an overall deterioration of social cohesion (WHO, 2020a). Along with the mental health strain of social isolation and fatigue from prolonged pandemic restrictions, reluctance and suspicion towards COVID-19 measures like vaccines has been shown to have a further negative impact on the mental health of Canadians (Pan et. al., 2024).

Given the role digital platforms and technology played throughout the COVID-19 pandemic, data extracted from these platforms during the pandemic can provide important insights into many different aspects of the COVID-19 pandemic response and public experience (Daghriri et al., 2022). This data has the potential to be used in the exploration of public sentiments in response to the pandemic, trends in government messaging during the

pandemic, and may provide valuable insights on misinformation tactics and how to best combat the spread of misinformation (Daghriri et al., 2022). With this data being the first opportunity to study technology and social media use during a global pandemic, the results may point to important considerations to leverage social media data to inform the preparation and planning of future pandemic response plans (Daghriri et al., 2022).

1.2 Literature Review

1.2.1 Introduction to Social Media Research

In the context of the COVID-19 infodemic, there are massive amounts of data from social media platforms available for analysis. This data has become an increasingly important tool within public health research (Daghriri et al., 2022). With the rapid evolution of social media, the emerging field of infodemiology has been utilizing methods of infoveillance to study search, communication, and publication behaviours on the internet (Eysenbach, 2009).

Studying social media data may allow public health professionals to identify facilitators and barriers to the spread of misinformation, strategies to improve social media communications, and understand the behaviours, opinions, and political leanings of a target population to maximize the efficacy of campaigns and the implementation of various policy measures (Daghriri et al., 2022, Eysenbach, 2009).

1.2.2 Social Media Data

When conducting social media research, machine learning and other techniques allow for the efficient processing and manipulation of large datasets (Tsapatsoulis & Djouvas, 2019). This empowers researchers to analyze massive, complex datasets efficiently (Tsapatsoulis & Djouvas, 2019).

Social media data offers a few key strengths that make it quite suitable for the monitoring and analysis of health behaviours and opinions. When studying temporal relationships, many data collection methods rely on the retrospective recall from participants; for example, a survey asking about policy changes over the last year would require

participants to remember their thoughts and feelings over that entire period. Relying on recall can lead to inaccuracies and bias being introduced to the study (Pan et al., 2024, Wang et al., 2022). Social media data can capture real-time data to better represent the sentiments and interactions on a platform at any given time organically, without the need for users to try and recall their thoughts and experiences (Pan et al., 2024, Vaillancourt et al., 2021). Social media data is also crowdsourced and can create much larger datasets given the large pool of users on the platforms (Vaillancourt et al., 2021). This data provides not only promptness but a level of flexibility, unlike most other sources, as social media allows for data to be collected in real time, from a broad spatial pool (Pan et al., 2024, Vaillancourt et al., 2021, Wang et al., 2022).

1.2.3 Methods for Social Media Analysis

There are a few popular methods for extracting data from social media, accessing the Application Programming Interface (API) allows researchers to extract public data (Longhurst, 2025). In the case of the Twitter API, researchers could filter tweets to extract based on characteristics like hashtags, keywords, or by selecting specific users (Longhurst, 2025). Once extracted, this data can be analyzed in many ways, including topic modeling, visual analysis, content analysis, geo-spatial analysis, evaluation of engagement metrics, and network analysis, to name a few (Pulsar, 2025). A popular tool used in social media research is VADER sentiment analysis (Geetha, 2023). VADER, or Valence Aware Dictionary for Sentiment Reasoning, is a lexicon and rule-based Natural Language Toolkit (NLTK) module that calculates a score to determine whether the sentiment of a piece of text is positive, negative, or neutral (Geetha, 2023). Sentiment analysis can be used to investigate customer reviews, and the emotions behind social media posts (Geetha, 2023).

Existing literature has used various machine learning techniques, including sentiment analysis of data from social media platforms to understand user opinions toward different topics during the COVID-19 pandemic such as policy changes, information communication, and opinions and personal experiences. Jalil et al. (2022) used various ML and deep learning techniques to study the sentiments of American Twitter users regarding increased levels of

fear toward the coronavirus. Niu et al. (2022) completed a similar study on COVID-related fear using Twitter data from Japan. The results of these studies suggest that increasing public awareness of the risks associated with COVID-19 infection increased the likelihood of people getting vaccinated, and that, in general, people supported the implementation of government lockdowns and social distancing measures (Niu et al., 2022, Jalil et al., 2022). However, the positive reception to these measures was only seen when government messaging was specifically targeted to combat misinformation circulating on a platform (Jalil et al., 2022).

1.2.4 Uses and Areas of Research

Research on public sentiments has been conducted across many industries. It has proven useful for research on crime prevention, emergency management, politics, brand marketing, health issues and illnesses, customer analytics, and for early prediction of changes in financial markets (Rodríguez-Ibáñez et al., 2023). As explained by Preethi et al. (2015), temporal sentiment analysis gives researchers the opportunity to investigate observed sentiments with other underlying events or circumstances. Not only does this allow for more effective use of the data, but it can also provide useful insight into patterns of human behaviours and how different events can produce changes in public opinions over time (Preethi et al., 2015).

When implementing a pandemic control framework, adherence to public health measures is crucial for the control and prevention of an infectious disease (WHO, 2020a). The efficacy of these measures is undermined when a population's behaviour is non-compliant (WHO, 2020a, WHO, 2020b). Existing literature has shown that factors impacting a population's adherence to public health measures include the availability of social and financial support, trust in government authorities, assertive communication, the regulation of social media, an underestimation of the risks and seriousness of a disease, and whether adherence is required for a prolonged duration (Krakowczyk et al., 2022, Rodríguez-Ibáñez et al., 2023, WHO, 2020b).

1.2.5 Impacts of Misinformation

Misinformation has been identified as a factor that can impact public sentiment and compliance with public health policies. Social media analysis is important for understanding the landscape of misinformation, and how it impacts public responses. In the review by Gabarron et al. (2021) of 22 studies investigating the proportions of COVID-19 misinformation on social media platforms, studies reported samples comprised of up to ~28% misinformation-containing posts. With evidence of a high amount of COVID-19 information on social media, it is crucial to study and understand the implications. Misinformation about statistics like incidence rate, prevalence, and other disease spread measures significantly altered the attitudes of the public during the pandemic and led to much more complacent attitudes towards the COVID emergency (Caceres et al., 2022, Krakowczyk et al., 2022). Furthermore, mis- and disinformation discouraged adherence to public health recommendations, reducing healthy behaviours like handwashing, and social distancing compliance (Tasnim et al., 2020). Misinformation also had more direct health impacts, encouraging dangerous pseudoscience, promoting the consumption of non-evidence-based treatments such as ivermectin and hydroxychloroquine, contributing to increased psychological distress (Perlis et al., 2023, Tasnim et al., 2020). The study by Perlis et al., (2023) found that individuals exposed to COVID-19 misinformation were significantly more likely to use these non-evidence-based medications, despite clear guidance from reputable health authorities warning against their use (Perlis et al., 2023).

1.2.6 Influential Accounts

Faced with the high public demand for information, and the dangers misinformation can cause, it is important to plan and evaluate the social media activity of influential accounts like health organizations and politicians.

Research like the studies by Hussain et al., (2022), Melton et al., (2022) and Marani et al., (2022) analyzed how social media users in both North America and Europe engaged in conversations specifically about the COVID-19 vaccine. Marani et al., (2022) investigated the contents of tweets published by public officials during the vaccine rollouts in Ontario,

British Columbia, and Alberta. They found that posts from these accounts were mostly used to communicate information to the public, an important finding given that public officials are likely to have more influence and reach than the accounts run by an average user (Marani et al., 2022). Most tweets from these officials were neutral in sentiment, with only 12% of public officials posting content with negative sentiments about the vaccine rollout (Marani et al., 2022). These accounts are especially important to consider when fighting misinformation as they are perceived to have a higher level of credibility and authority, meaning that they can be key channels for debunking rumours, or can cause significant damage if they engage in the spread of misinformation (Gabarron et al. 2021, Marani et al., 2022).

1.2.7 Outcome Monitoring

Social media data and research can act as an important tool for engaging with and understanding the needs and behaviours of a population. It also acts as a channel for promoting public health initiatives and sharing information. Analysis of social media data can be used to design targeted communication strategies and design policy measures that will decrease rates of vaccine hesitancy, distrust, and resistance to government mandates, and ultimately lead to improved health outcomes over time (Daghriri et al, 2022, Rodríguez-Ibáñez et al., 2023).

In addition to understanding the behaviours and opinions expressed online, social media data can act as a key tool for ongoing health monitoring and outcome analysis. Pan et al., (2024) effectively demonstrated the importance of public sentiment and social media engagement for understanding the public experience during a public health emergency. Their study used geotagged tweets to conduct geospatial analysis on mental health during the pandemic, and the facilitators of mental wellness (Pan et al., 2024). This study identified “fear” and “sadness” as the most prevalent emotions expressed on X (formerly Twitter) throughout the pandemic, with “trust” and “anticipation” being the most used positive terms, though these became less prevalent over time (Pan et al., 2024). A key strength of this study is that they were able to demonstrate how social media data can also be utilized for granular analysis, using location data to investigate regional differences (Pan et al., 2021).

Interestingly, this study found geospatial differences in mental health trends, again displaying the utility of this data on a broad and region-specific scale (Pan et al., 2024). Literature has also identified barriers and facilitators of positive mental health outcomes during the pandemic using social media data, identifying disability and illness, income level, ethnicity, gender identity, migrant status, urbanicity (specifically the accessibility of near green space) and the disruptions to regular life caused by the pandemic as being linked to mental health issues in Canadian populations (Jenkins et al., 2022, Evra & Mongrain, 2020, Pan et al., 2024).

There is significant literature demonstrating the utility of social media data for understanding population health topics, in relation to the pandemic, mental health outcomes have been of particular interest (Effenberger et al., 2020, Pan et al., 2024, Udea et al., 2023). The work by Udea et al. (2023) created a machine learning framework used to monitor near-real-time social media data to monitor trends of emotional distress during the COVID-19 pandemic. Frameworks like this create opportunities for quick monitoring of health topics of interest, in this case emotional distress and suicidality of social media users, and can handle continuous measurement data, allowing for near-real-time updating results (Udea et al., 2023).

The research by Effenberger et al. (2020) utilized Google Trends to investigate a possible relationship between trends in Google searches and COVID-19 case counts to model disease spread, predict, and identify outbreaks quickly. This research highlighted that infoveillance using public interest manifesting through patterns in search queries is a useful indicator of outbreak progression in a population, after discovering the highest Google search interest in the virus, correlated to a time lag-predicted peak of cases counts during an outbreak (Effenberger et al., 2020). Another example of disease spread monitoring, and the broad spatial range of social media data can be seen in the study by Bisanzio et al. (2020), who utilized Twitter data to analyze human mobility to predict spread patterns. In their research, Twitter users in the study cohort travelled to 28 countries (Bisanzio et al., 2020). Of the 82 COVID-19 cases that had been reported outside of China at the end of January

2020, 54 cases had tagged geolocation coordinates; 74.1% or 40 cases were reported within 15km from a location visited by at least one member of the study cohort (Bisanzio et al., 2020).

1.2.8 Relevance and Gaps in Current Literature

While research on social media sentiment during the COVID-19 pandemic is growing, thus far, much of the literature base has centered on the mental health outcomes and psychosocial experiences of individuals navigating the uncertainty, isolation, fear, and mistrust expressed by the public throughout the pandemic. Numerous studies have explored the emotional toll of the pandemic, examining anxiety, depression, and stress as reflected in platforms like Twitter, Facebook, and Reddit (Jenkins et al., 2022, Pan et al., 2024, Udea et al., 2023).

In parallel, substantial literature has investigated the underlying variables that shape sentiments, including vaccine hesitancy and risk perception to digital trust, misinformation, and the influence of media framing (Krakowczyk et al., 2022, Perlis et al., 2023, Tasnim et al., 2020). Studies consistently highlight the widespread impact of misinformation on public behavior and trust in institutions, as well as the role of emotional contagion in shaping collective discourse online (Krakowczyk et al., 2022, Perlis et al., 2023, Tasnim et al., 2020). Some work has also been done to evaluate public health campaigns and the behaviours and roles of “authority” figures in fighting misinformation (Gabarron et al. 2021, Marani et al., 2022).

However, despite this rich exploration of behavioral and emotional dynamics, there remains a notable gap in research that focuses explicitly on how public sentiment changes in relation to government policy interventions, particularly the stringency of these measures over time. Few studies examine the temporal connection between specific policy strictness levels and fluctuations in public sentiment across platforms (Chum et al., 2021, Daas et al., 2024). While some research does study policy stringency and sentiment, this has not focused on Canadian data, and like most of the literature, represented data from the earliest months of the pandemic, thus missing important insights and potential changes seen after the pandemic

had been ongoing for a number of months. This research has not yet investigated geospatial differences in the policy–sentiment relationship (Chum et al., 2021, Daas et al., 2024).

This thesis aimed to address these gaps, investigating potential relationships between sentiments on various policies and the associated stringency levels from late 2020 to mid-2021 in Ontario, Canada. The research also aimed to identify differences in the emotional responses displayed between Twitter users in the two largest cities in Ontario.

Chapter 2: Research Questions

2.1 Trends and Changes in Public Sentiment Scores

This thesis sought to investigate factors effecting public sentiments expressed on Twitter by users in Ontario about the COVID-19 pandemic and associated public health policy measures implemented over the second and third waves of the pandemic. This research investigated the sentiments of tweets posted on topics related to key pandemic interventions, lockdown measures, masking measures, and vaccine mandates.

2.2 Investigate Contextual Factors and Policy Stringency

In addition to changes in policy measures, this study also considered the impact of the relative strictness of various pandemic policies. These factors were investigated to measure possible relationships to identify policy types and levels of strictness that are most likely to be well received by the public upon implementation.

2.3 Compare Sentiment Scores for Public Health Interventions By Location

Finally, this research investigated variations in sentiment score trends based on the locations of Twitter users. Separate analyses were conducted on data from users identified as being from Toronto and those from Ottawa during the study timeframe. This allowed for comparisons of public sentiment trends between the populations of Ontario's two largest cities across the policy categories of interest.

Chapter 3: Methods

3.1 Study Design

This study utilised an ecological study design to conduct observational, infoveillance research. It analyzed data from Twitter users in Ontario, Canada, spanning the timeframe of December 2020 to June 2021. These dates were relevant given that they capture the heights of the second and third waves of the pandemic in Ontario (some of the largest waves) (CIHI, 2022, PHO, 2023).

3.2 Description of Datasets and Sample

Research ethics approval for this study was obtained from the University of Waterloo Research Ethics Board (ORE # 46591). The data used in this study was extracted from the Twitter Application Programming Interface (API) and is comprised of English Twitter posts written between December 2020 and June 2021 by users who were located in Ontario. The timeframe of the dataset was chosen both due to availability and because it captures the heights of the second and third waves of the COVID-19 pandemic in the province, which spanned between September 2020 - February 2021 and March 2021 - July 2021, respectively (PHO, 2023).

The initial Twitter data was retrieved using keywords and hashtags, including “covid” (and variations like “coronavirus”, “covid-19”, and “pandemic”), “vaccine” (and variations like “vaccines”, “vax”, “vaccination”, “Pfizer”, “Moderna”, “shot”, “jab”, and “AstraZeneca”), and COVID symptoms (like “cough”, “running nose”, and “shortness of breath”).

This study sample will include Twitter users who posted at least once on the app during the study period, with the content of that post being related to the COVID-19 pandemic measures of interest. Given this is an observational study meant to examine the population rather than the individual experience, it did not attempt to sample based on demographic information beyond limiting to users in the province of Ontario, who post content on Twitter in English. This was also necessary given the use of Twitter data as it would be essentially impossible to reliably extract the demographic information of the user

profiles included in this study from their social media accounts. It could be assumed that the sample consists of individuals in Ontario, over the age of 13 (the minimum age required to create a Twitter account), who have access to a phone or computer and the internet to be capable of engaging on Twitter. Given this study used retrospective data that is publicly available to be extracted using keyword searching from the Twitter API and various publicly available indexes and timelines, a further recruitment plan was not required.

All data processing, analyses, and visualizations were conducted using Python in a Jupyter Notebook kernel. Before analysis, the monthly Twitter datasets required pre-processing (see Figure 1 for a flowchart of data pre-processing), where the data would be “cleaned” to allow for effective analysis. This processing entailed the removal of unnecessary components of each tweet, including any special characters, links, and mentions. The pre-processing also removed duplicate and blank tweets from the dataset, as well as retweeted posts. Base forms were used to replace synonyms and abbreviations. After pre-processing, the remaining tweets included for analysis contained anonymized data within the following parameters:

Table 1: Remaining tweet data after data pre-processing.

Parameter	Description
author_id	A unique ID for each Twitter user’s account
id	A unique ID assigned to each collected tweet. If a user posted multiple tweets with the keywords, it will count each tweet.
Text	The contents of the tweet
Favourite/Like_count	The number of likes from the tweet
Retweet_count	The number of retweets from the initial tweet
Time	Provides the day, month and year of posted tweet
User_location	Provides the geo-tagged location of the user
User_created_at	Provides the date and time that the Twitter user account was created.

3.3 CIHI COVID-19 Interventions Dataset

The Canadian Institute for Health Information (CIHI) maintained a comprehensive data set on the COVID-19 pandemic interventions implemented by the federal, provincial, and territorial governments (CIHI, 2022). This open-access dataset is available through both an interactive timeline on the CIHI website, and a downloadable Excel spreadsheet (CIHI, 2022). The dataset contains data on interventions collected between March 2020 and May 2022, with the last data tables being released on October 13, 2022 (CIHI, 2022).

A subset of the data parameters was outlined in a table (see Appendix A) to refer to for analysis. The table contains information on interventions that fall into the three policy categories of interest for this study, with the far-right column being added to clearly label the category each intervention applies to (CIHI, 2022).

In addition to providing definitions of regulations that fall into the categories of interest (vaccines, masking, and lockdowns), the CIHI COVID-19 Intervention Data has been used to create an interactive tool reporting the timeline of COVID-19 policy changes, detailing the implementation and lifting of restrictions. This dataset and timeline were used to inform the creation of the events overlay to compare with the average daily compound sentiment analysis data (CIHI, 2022).

3.4 COVID-19 Stringency Index

The COVID-19 Stringency Index is a tool developed and updated by the Centre of Excellence on the Canadian Federation to track and evaluate provincial pandemic responses. This index was intended to create an objective method of analysis to evaluate provincial responses since policies and standards were constantly changing, and response plans varied significantly from province to province (Sim, 2021). The index uses a numerical coding scheme to measure the relative stringency (restrictiveness) of COVID-19 response measures enacted by provincial and territorial governments throughout the pandemic (Centre of Excellence on the Canadian Federation, 2021). When first released, the index covered 12 public health measures but was updated to include a total of 17 different response categories

(Centre of Excellence on the Canadian Federation, 2021). The updated coding scheme for the 17 measures covered in the index can be found in Appendix B.

The stringency index can be used to explore provincial variations in timing, relative stringency of provincial and territorial government responses, and can be used to model policy changes over time (Sim, 2021). The index dataset spans from March 1, 2020, until September 20, 2022. The scale of the stringency index spans 0-100; the higher the stringency score, the higher the relative strictness of the policies (Centre of Excellence on the Canadian Federation, 2021). The index includes multiple stringency sub-indices. This study initially considered two indices that report on the overall policy settings for both non-vaccinated and vaccinated people, with one index representing the simple average and the other representing the weighted average. The simple average sums the vaccinated and non-vaccinated indices and divides by two (Centre of Excellence on the Canadian Federation, 2021). The weighted average index uses the proportional population vaccination status, classifying those with an initial vaccine protocol as “vaccinated” to weight the values (Centre of Excellence on the Canadian Federation, 2021). Given the timeframe of this study, these figures were equal throughout the study period as COVID vaccination efforts in Canada were only just beginning, meaning the number of fully vaccinated individuals in the population was too small to be significant, thus the simple index was ultimately chosen.

3.5 Zero-Shot Classification

Zero-shot classification was performed on the cleaned, processed monthly datasets. This is a machine learning technique that enables models to categorize data into predefined labels without the need for task-specific training data (Van Otten, 2024). Instead, it used knowledge from large-scale, pre-trained models and semantic relationships to assign the most appropriate label to data from a chosen set (Van Otten, 2024). Zero-shot classification was used in this case because the policy categories of interest for this study were pre-determined, and there was no available, pre-existing labeled data to use for model training. After testing the selected labels on a smaller data subset, the following category labels were chosen: 1. Vaccine Mandate, 2. Mask Policy, 3. Lockdowns, 4. COVID General, 5. Unrelated. The

“unrelated” category was then used to filter and exclude irrelevant tweets from the monthly datasets.

3.6 Sentiment Analysis

After the data pre-processing and zero-shot classification, sentiment analysis was run on the filtered datasets using VADER sentiment analysis. VADER calculated individual sentiment scores for each tweet in the dataset using a comprehensive lexicon containing around 7,500 features. This dictionary includes phrases, words, emoticons, and acronyms (Ma, 2022).

Sentiment calculations are made by classifying the features in a piece of text as either “negative”, “positive”, or “neutral” based on their scores in the lexicon, giving percentages of each classification feature; features not listed in the lexicon are marked with a score of “0” or in other words, a “neutral” score (Ma, 2022). VADER scans for sentiment features, modifies for rules of polarity and intensity, and sums the sentiment score features. The final score is then normalized to (-1, 1) using the function:

$$xx2 - \sqrt{+axx2 + a}$$

(Ma, 2022, Mohamad, 2023).

When interpreting a VADER compound sentiment score, a score of -1 denotes an extremely negative text, and a score of +1 represents an extremely positive text (Hallett, 2022). The thresholds typically used when interpreting a compound sentiment score classify a positive score as ≥ 0.05 , and a negative score as ≤ -0.05 ; text with a score that lands within the threshold of ≥ 0.05 and ≤ -0.05 would be considered to have neutral sentiment (Hallett, 2022). These same interpretation thresholds were used for this study. For this study, compound sentiment scores, or the summed total of the scores assigned to all features in a text, were used for analysis.

VADER was chosen as the appropriate method for this project given it is particularly well-suited for the sentiment analysis of social media data. Unlike other methods, VADER was designed with the intention for use in social media analysis and performs best when detecting sentiments in short pieces of text like a tweet or comment (GeeksforGeeks, 2025).

The tool is also capable of handling slang, abbreviations, and emojis – pieces of text that can provide important nuance into the context and meaning of a social media post (GeeksforGeeks, 2025). The flowchart illustrated in Figure 1 outlines the steps taken to process and prepare the data for analysis.

3.7 Manual Validation

To determine the accuracy of the VADER sentiment analysis and zero-shot classification, manual validation was conducted on a random sample of tweets from each topic, testing their calculated sentiment scores and the accuracy of the topic labelling (Libretexts, 2023).

The sample size for manual validation was calculated using the following equation:

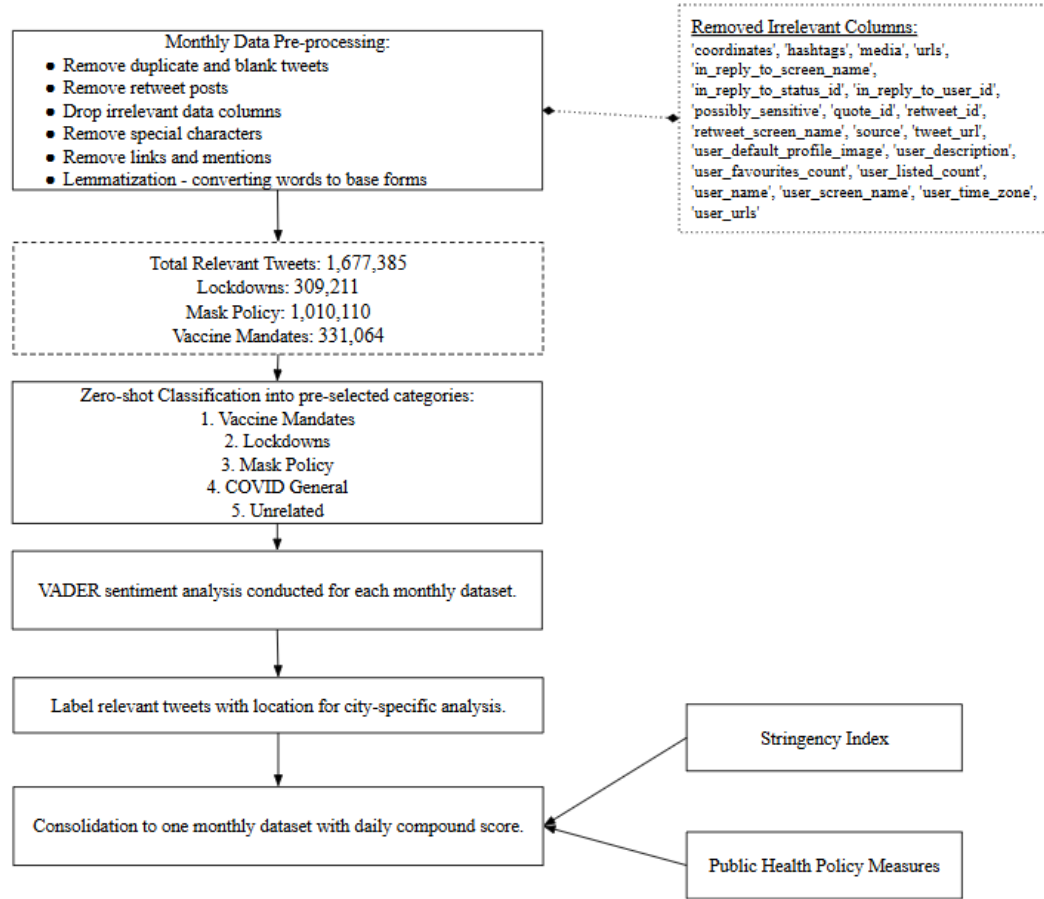
$$n = \frac{Z^2 * p * (1-p)}{E^2} = \frac{(1.96)^2 * 0.5 * (0.5)}{0.5^2} = 384.16$$

Results and details from manual validation can be found in Appendix D.

3.8 Summary Statistics Dataset for Analysis

Once each tweet in the dataset was assigned its compound sentiment score, the monthly datasets were combined into one large spreadsheet, containing daily summary data. This included a daily average compound sentiment score for each day in the study period, for each of the policy categories assigned during zero-shot classification, excluding the “Unrelated” category. This summary dataset was then merged with the average stringency index values scored by policies on a given day. This was the summary data used for further exploration and analysis.

Figure 1: Flowchart of Data Pre-processing



3.9 Summary and Visual Analysis

The daily average sentiment score data was plotted over time, visualizing trends in sentiment scores through the second and third pandemic waves. Important events were investigated, referring to the timeline in the CIHI interventions dataset to identify key dates and policy alterations. Dates with major policy changes or scientific breakthroughs were overlaid on the temporal sentiment trend data to explore potential interactions and key changes that led to significant changes in public sentiment expressed on Twitter. Visual analysis was also conducted on city-specific subsets of the data to investigate differences in the reactions of Twitter users located in Ottawa and Toronto.

3.10 Statistical Analysis

Given that this study used social media data, it was expected that there would likely be a lag between a variable change and the manifestation of a behaviour; thus, piecewise regression was performed to study relationships between pandemic policies and sentiment scores to account for these delays in responses (Nguyen et al., 2012). Lag intervals of 3, 7, and 14 days were chosen for use in analysis to capture relatively immediate responses, as well as reactions that take longer to manifest (Nguyen et al., 2012). Twitter data has demonstrated to be quite reactive, thus a 3-day lag was deemed appropriate for capturing the near-immediate responses of users to policy changes (Nguyen et al., 2012). While literature has shown that these immediate reactions diminish quickly as user focus tends to move on quickly, longer lag intervals of a week and two weeks were applied to investigate persistence in the responses to policy changes over a longer time span (Nguyen et al., 2012).

The piecewise regression models incorporated policy stringency to investigate the potential impacts of stringency on sentiments expressed by Twitter users over the study period. This method was well-suited for this study because of its ability to capture changes in variable relationships at distinct thresholds, otherwise known as “breakpoints” (Muggeo, 2003). These breakpoints were of interest due to their potential to identify points at which certain policies became too strict or otherwise less socially acceptable to understand if and how public sentiments changed as stringency levels increased.

During analysis, each model was analyzed using the “optimal breakpoint” which were determined by testing multiple candidates and selecting the one with the lowest Akaike Information Criteria (AIC) value (Muggeo, 2003). This approach aimed to find a meaningful threshold relationship. Piecewise regression allows for flexibility to set multiple breakpoints depending on the best choice for the data. Given that this data had a limited range of stringency scores, only one breakpoint was implemented. This decision helped maintain model interpretability and focused the investigation on the most significant change point in the data.

After piecewise regression, pieced ridge regression was also applied to the data using the previously defined optimal breakpoints. This step was taken to address potential issues of multicollinearity and overfitting in the regression models. Ridge regression applied a penalty to the coefficients, shrinking them to prevent overfitting of the model (Lu & Chang, 2023). Combining this with piecewise analysis gives it the flexibility to also capture non-linear trends by investigating different segments of the data.

In addition to the full-sample analysis, subset analysis was performed focusing exclusively on tweets originating from Twitter users located in Toronto or in Ottawa. This analysis followed the same analysis methods, aside from geographic filtering. Piecewise regression models were again estimated for 3-, 7-, and 14-day lag intervals for each policy category, allowing for a comparative assessment of the sentiment trends exhibited between the two cities.

Chapter 4: Results

After pre-processing and sentiment analysis, the total number of tweets across the timeframe deemed relevant to the three policy categories was 1,677,385, with 2,428,230 tweets if including the COVID General bin. The lockdown category accounted for 309,211 tweets, vaccine mandates had 331,064 tweets, and mask policy had significantly more relevant tweets, with a total of 1,010,110. The COVID General category contained 778,845 tweets. A full breakdown of the monthly tweet frequencies can be found below in Table 2. Tweet activity varied over time, with activity peaking across categories in April 2021 with 378,235 total monthly relevant tweets, as seen in Figure 2. June 2021 had the lowest relevant tweet frequency, with only 141,033 total relevant posts.

Table 2: Summary of results from data processing

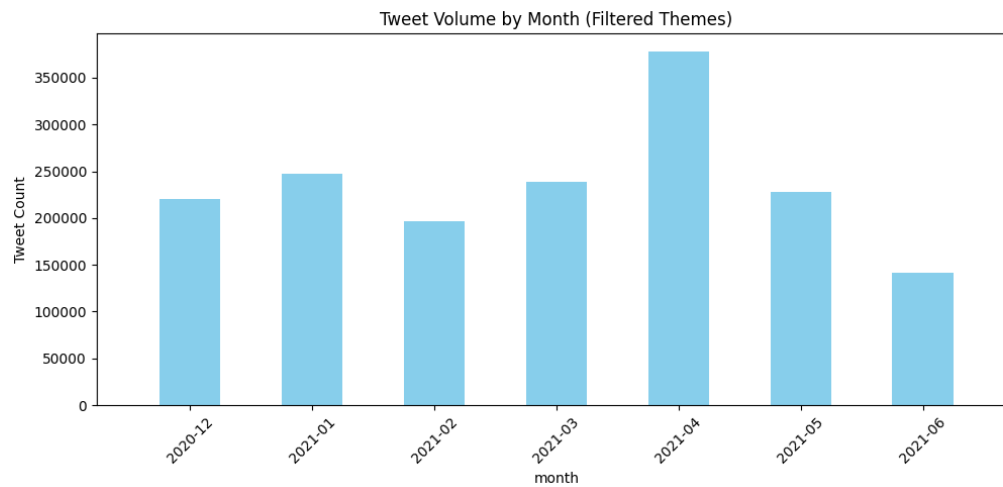
Month	Total Tweet Count	Lockdowns	Mask Policy	Vaccine Mandates	COVID General
Dec. 2020	n=327,924 r=220,107	n= 49,158 s=0.026151	n= 139,950 s=0.043529	n=30,999 s=0.123938	n=107,817 s=0.095602
Jan. 2021	n=365,205 r=274,550	n=55,575 s=0.004971	n=155,668 s=0.017020	n=36,307 s=0.095929	n=117,655 s=0.053708
Feb. 2021	n=292,368 r=196,497	n=37,704 s=0.017233	n=125,759 s=0.045668	n= 33,034 s=0.100128	n= 95,871 s=0.076425
Mar. 2021	n=349,148 r=239,070	n=37,220 s=0.014705	n=145,270 s=0.057915	n=56,580 s=0.107672	n=110,078 s=0.091447
Apr. 2021	n=548,346 r=378,235	n=72,673 s=-0.022391	n=221,138 s=-0.001375	n= 84,424 s=0.087242	n=170,111 s=0.056367
May. 2021	n=336,391 r=227,893	n=36,602 s=0.003498	n=136,310 s=0.041355	n=54,981 s=0.126320	n=108,498 s=0.099933
Jun. 2021	n=208,848 r=141,033	n=20,279 s=0.007266	n=86,015 s=0.059145	n= 34,739 s=0.143655	n=67,815 s=0.122634

*n = number of tweets

**s = average monthly compound sentiment

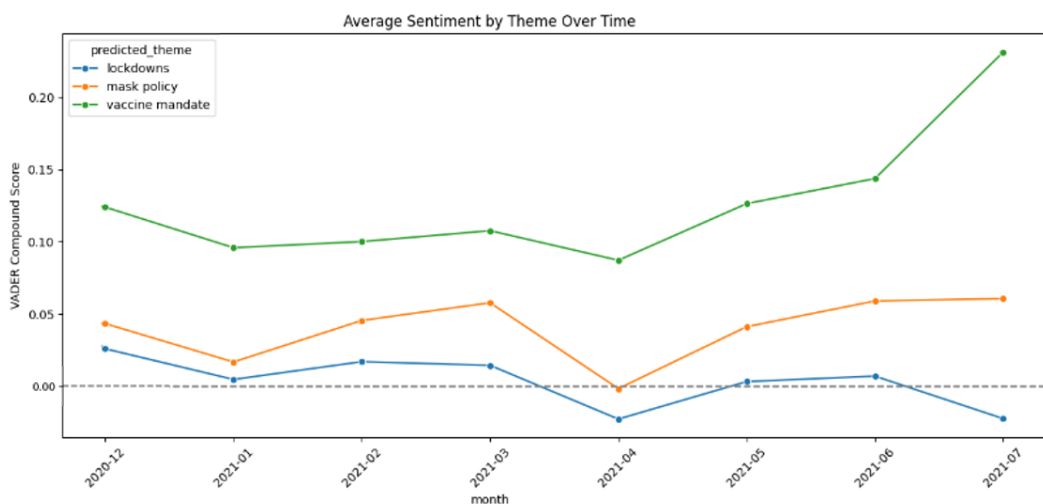
***r = number of tweets relevant to the study (removing “covid general” from total count)

Figure 2: Monthly Tweet Volume (for three relevant policy categories)



Comparing the monthly sentiment score averages for each tweet category illustrated in Figure 3, vaccine mandates scored the highest and averaged the most positive scores throughout the timeframe. Mask policies scored lower, with monthly averages hovering right around the threshold of positivity, and a few notable dips to neutral sentiment in January and April. Lockdowns had the lowest monthly averages consistently in the neutral range.

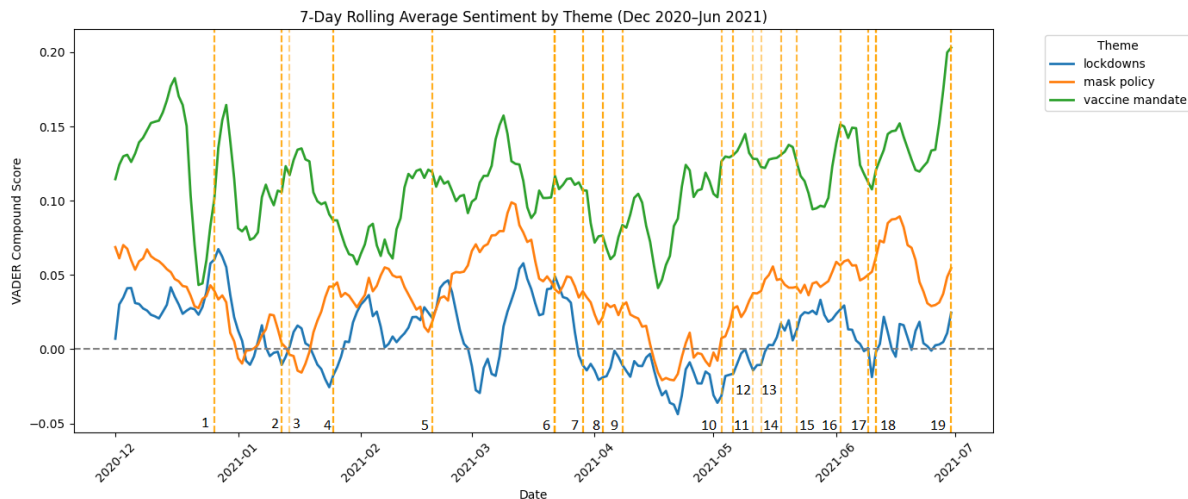
Figure 3: Average Monthly Sentiment Per Theme Line Graph



4.1 Objective 1: Sentiment Trends Over Time

When analyzing the 3- and 7-day rolling averages as seen in Figure 4, the average daily compound sentiment scores of Twitter posts about all three of the COVID-19 policy categories remained mainly neutral or positive across the study timeframe. The tweets in the vaccine mandate category consistently exhibited the highest levels of positivity, with the rolling averages for the vaccine mandate category barely slipping into the neutral threshold, let alone down to negative levels. The positivity of mask policy-related sentiments was more moderate, with the rolling average fluctuating between positive and neutral scores, with a few dips to a slightly negative level. Lockdown-related tweet sentiments scored the lowest throughout the timeframe, mostly remaining within a neutral score range, with a few drops to the negative level. As seen in Figure 4 and the 3-day rolling monthly trend data in Appendix C, lockdowns also had the least variation in the average daily compound sentiment data, with the trend lines exhibiting less severe peaks and valleys across the study period.

Figure 4: 7-day Rolling Sentiment by Theme with Events Overlay



When comparing the trends over time to key policy changes, there appear to be some connections when consulting Appendix C. Some event lines that appear to align with peaks and valleys in the data include December 26, when a province-wide shutdown with additional restrictions was imposed. January 12-14 showed drops in sentiments around mask

mandates, in this period, there were several significant policy changes, including masking for children in schools, recommending mask use outdoors, and declaring a province-wide state of emergency on January 15th. On March 25th, the government announcement of CERB appears to align with an increase in positivity, especially for the lockdown and vaccine-related tweets. Around April 3rd and 8th there are noticeable declines in lockdown sentiments, aligning with the use of the emergency brake lockdown, and the declaration of another province-wide state of emergency. May sentiment scores remained relatively steady; from a policy perspective, the month was shaped by a period of gradual reopening and loosening of restrictions. June displayed more variability with the most noticeable peak at the end of the month, at the same time, the province entered the second phase in the Roadmap to Reopening, loosening numerous restrictions (Centre of Excellence on the Canadian Federation, 2021).

4.2 Objective 2: Regression Analysis

4.2.1 Lockdowns

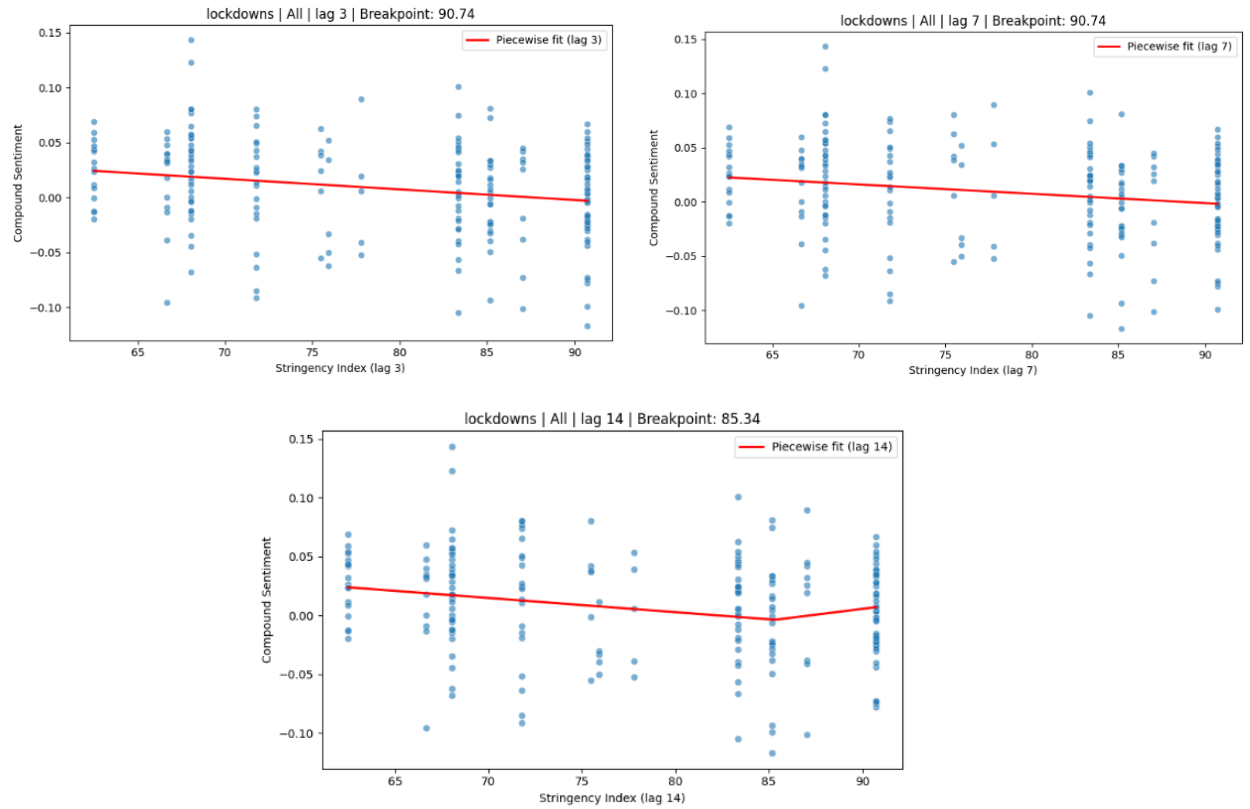
4.2.1.1 Piecewise Regression

A summary of the results for the lockdown piecewise regressions can be found in Table 3. All three lagged models were statistically significant ($p < 0.02$), but with small R^2 values (~ 0.05), suggesting the proportion of the variance in sentiment scores accounted for by the models was the smallest of the three models (between 4.8%-5.7%). All Piece1 lags showed negative effects on sentiment ($\beta = -0.0009$ to -0.0012 , $p < 0.009$). Given the high breakpoint (90.74), there was no estimatable data for Piece2 in the 3- or 7-day models. The 14-day lag Piece2 was also weak and insignificant ($p = 0.278$). The date variable did not show a significant relationship in any of the models ($p > 0.166$). Along with the lack of significance the date variable had on the sentiment scores, stringency appeared to have very little impact on the public sentiments expressed regarding lockdown measures.

Table 3: Lockdowns Piecewise Regression – All Locations

Metric	3-Day	7-Day	14-Day
Optimal Breakpoint	90.74	90.74	85.34
R-squared	0.057	0.048	0.053
Prob (F-statistic)	0.00237	0.00619	0.0105
Piece1 Coefficient	-0.0010	-0.0009	-0.0012
Piece1 p-value	0.003	0.009	0.005
Piece2 Coefficient	2.684e-15	0	0.0020
Piece2 p-value	< 0.0001	0	0.278
Date_num coefficient	-4.372e-05	-4.563e-05	-8.347e-05
Date_num p-value	0.405	0.391	0.166
Durbin Watson	1.432	1.426	1.416
Jarque-Bera p-value	0.105	0.0840	0.254

Figure 5: Piecewise Regression Graphs for Lockdown-related Tweets



4.2.1.2 Ridge Regression

When applying pieced ridge regression, the models showed predictive power given their low MSEs (0.0022, 0.0023). All three Piece1 coefficients suggested a negative trend in sentiment scores up to the breakpoints. The 3- and 7-day lags were again not estimatable given the high breakpoints, but the 14-day lag indicated a slight upturn in sentiments after reaching the threshold. This reinforces the patterns seen in the initial regression analysis. Interestingly, the 14-day lag Piece2 coefficient was larger than that in Piece1, suggesting that the relationship between the variables may be significant; this differs from the piecewise regression as the 14-day Piece2 coefficient was not statistically significant. The date variable coefficients were negative, but very small, pointing to a very slight, potential decrease in sentiment over time regardless of policy stringency levels.

Table 4: Ridge Regression: Lockdowns – All Locations

Lag Interval	Breakpoint	Alpha	MSE	Piece1 Coef	Piece2 Coef	Date_num Coef
3-day	90.74	10.0	0.0022	-0.00074	0	-0.00008
7-day	90.74	10.0	0.0023	-0.00077	0	-0.00007
14-day	85.34	10.0	0.0023	-0.00133	0.00299	-0.00013

4.2.2 Vaccine Mandates

4.2.2.1 Piecewise Regression

Considering the piecewise regression for vaccine mandates, summarized in Table 5 and illustrated in Figure 6, all models were statistically significant ($p < 0.001$). The 3-day lag showed the best model fit ($R^2 = 0.131$), suggesting policy stringency accounted for 13.1% of the variance in sentiment scores. The Piece1 results show a significant drop in sentiment scores, particularly for the 3- and 7-day lags ($\beta = -0.0101, -0.0114, p < 0.0001$), suggesting that increases in stringency at lower levels caused sentiment to become more negative. Piece2 data for these periods did not show additional significant score changes after the

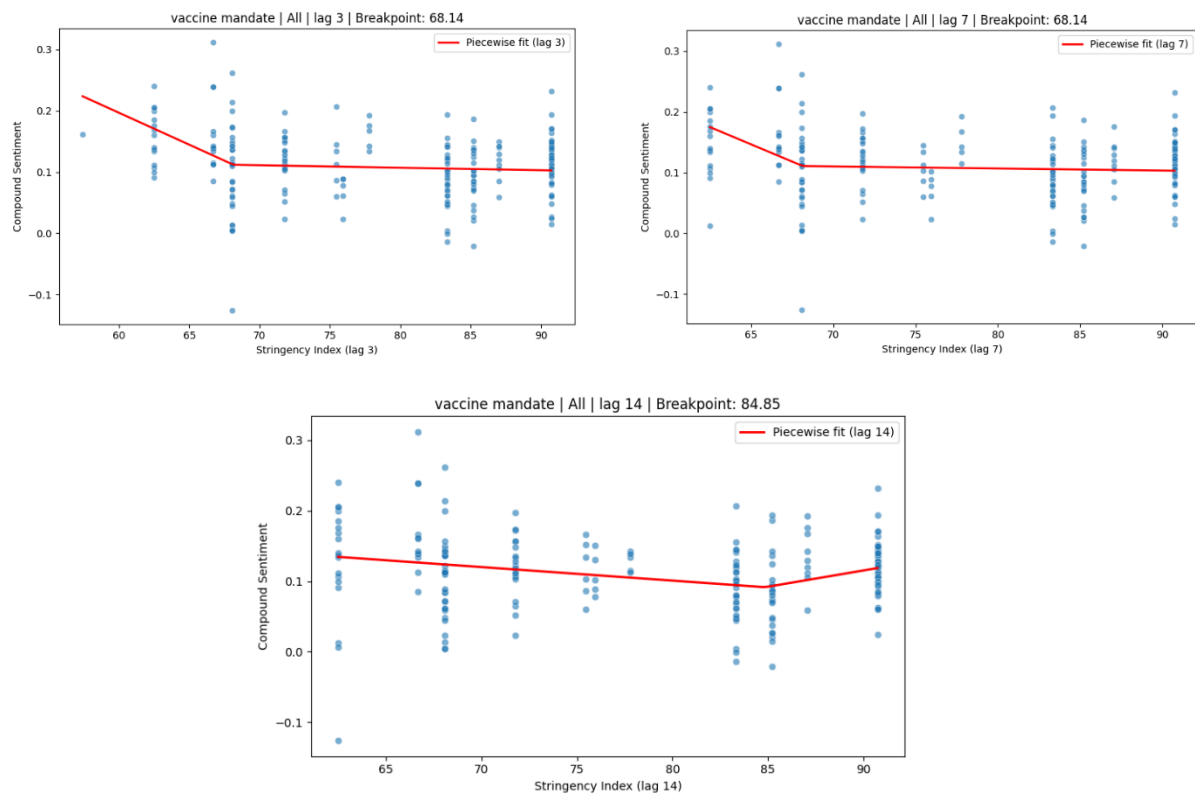
breakpoint (68.14) for the shorter time lags. For the 14-day lag, the model exhibited positive changes in score ($\beta = 0.0046$, $p = 0.029$) after the breakpoint (84.85), meaning that after hitting the stringency breakpoint of 84.85, sentiments stabilized, and with a two-week lag, sentiment scores showed a positive shift even with policies raised to a higher strictness level.

The date variable was statistically significant and positive for the 3- and 7-day lag models ($\beta = 0.002$, 0.003 , $p < 0.001$). The 14-day lag model for the date variable was not significant ($p = 0.131$). These results suggest that, regardless of policy changes, public sentiments toward vaccine mandates trended slightly positively over time.

Table 5: Vaccines Mandates Piecewise Regression – All Locations

Metric	3-Day	7-Day	14-Day
Optimal Breakpoint	68.14	68.14	84.85
R-squared	0.131	0.122	0.081
Prob (F-statistic)	2.47e-06	6.32e-06	0.000615
Piece1 Coefficient	-0.0101	-0.0114	-0.0019
Piece1 p-value	< 0.0001	< 0.0001	< 0.0001
Piece2 Coefficient	-0.0004	-0.0003	0.0046
Piece2 p-value	0.362	0.451	0.029
Date_num coefficient	0.0002	0.0003	0.0001
Date_num p-value	< 0.0001	< 0.0001	0.131
Durbin Watson	1.183	1.094	1.065
Jarque-Bera	8.81e-06	4.21e-06	3.99e-12

Figure 6: Piecewise Regression Models for Vaccine Mandate-related Tweets



4.2.2.2 Ridge Regression

The piecewise ridge regression models (Table 7) all had small MSEs (0.0034 - 0.0044), suggesting the model has prediction capabilities. All three Piece1 coefficients were negative, indicating that up to the thresholds, sentiment scores trended negatively towards vaccine mandates. Piece2 coefficients were negative in the two shorter lags, but, like the initial regression analysis, showed a positive upturn in sentiment in the 14-day lag. This ridge regression reinforces that stringency does have an impact on vaccine mandate sentiments, and that, regarding vaccine mandates, the population sentiment seems to rebound and show acceptance of the policy over time.

Table 6: Ridge Regression: Vaccine Mandates - All Locations

Lag Interval	Breakpoint	Alpha	MSE	Piece1 Coef	Piece2 Coef	Date_num Coef
3-day	68.14	10.0	0.0038	-0.00762	-0.00101	0.00019
7-day	68.14	10.0	0.0040	-0.01007	-0.00097	0.00024
14-day	84.85	10.0	0.0044	-0.00275	0.00665	0.00005

4.2.3 Mask Policies

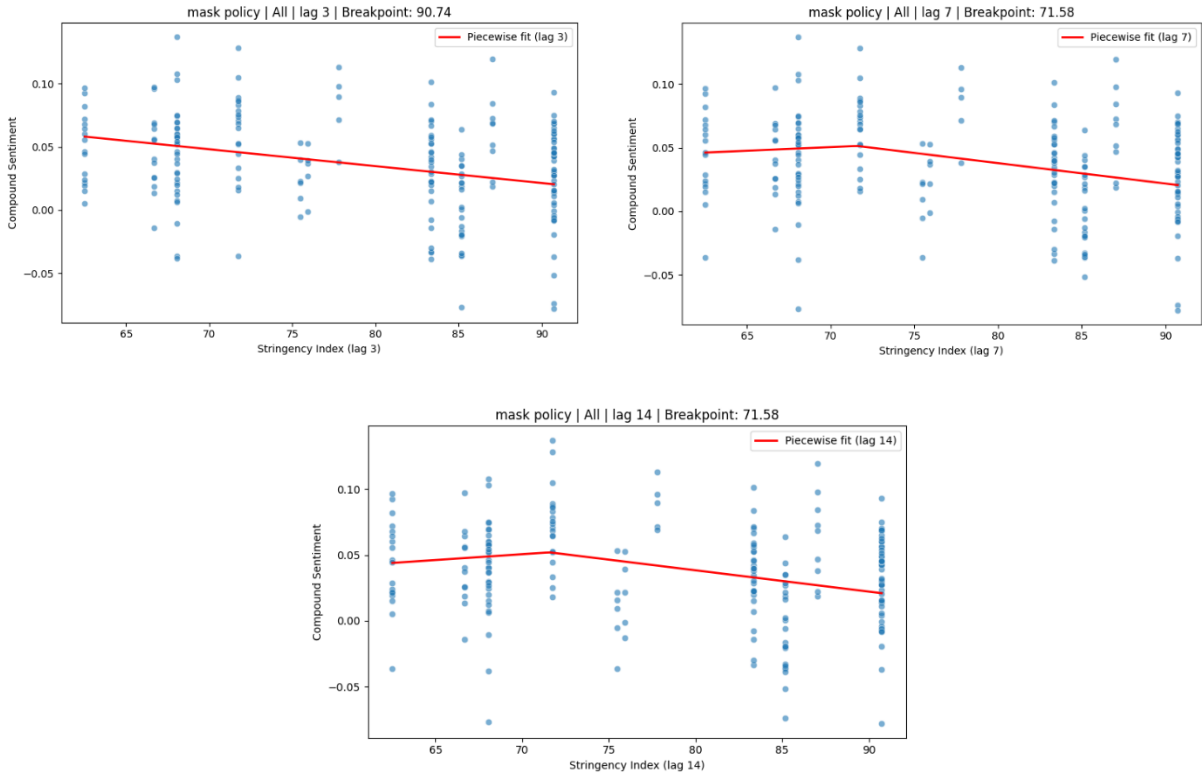
4.2.3.1 Piecewise Regression

The 3-day lag model (Table 8) again showed the best fit of the three lags in the mask policy data ($R^2=0.122$), meaning the model explained 12.2% of the variance in the sentiment scores. The piecewise regression models all demonstrated significance ($p < 0.000135$). Piece1 showed a slight negative effect on sentiment in the 3-day lag ($\beta = -0.0013$, $p < 0.0001$), and a positive but insignificant impact in the 7- and 14-day lag models ($p > 0.45$). Given the high breakpoint (90.74), there was no estimatable data for the 3-day model for Piece2. In the longer lag intervals, Piece2 demonstrated statistically significant negative changes ($\beta = -0.0016$, $p < 0.0001$). These results show that the immediate public reaction to mask policies was negative regardless of the strictness of the policies. The longer lag models seem to point to an erosion in mood, with stronger negative reactions occurring after the longer time lags. The breakpoints for the longer lag models were also lower, suggesting that over time, public sentiment shifted directions at lower stringency levels, again suggesting that quick reactions were negative with the increase in policy stringency. After a longer lag from the policy change, reactions were slightly increasing in sentiment (positive); however, in the longer lag models, the breakpoints were lower and once met, the sentiments trended more negatively than in the 3-day model. The date variable regression model showed the date interaction to be very slightly positive and significant in all models ($\beta = 0.0001$, $p < 0.0035$), again showing a very gradual upward trend in public sentiment over time.

Table 7: Piecewise Regression Mask Policies – All Locations

Metric	3-Day	7-Day	14-Day
Optimal Breakpoint	90.74	71.58	71.58
R-squared	0.122	0.101	0.095
Prob (F-statistic)	1.53e-06	7.19e-05	0.000132
Piece1 Coefficient	-0.0013	0.0006	0.0009
Piece1 p-value	< 0.0001	0.631	0.456
Piece2 Coefficient	0	-0.0016	-0.0016
Piece2 p-value	0	< 0.0001	< 0.0001
Date_num coefficient	0.0001	0.0001	0.0001
Date_num p-value	0.001	0.002	0.003
Durbin Watson	1.163	1.168	1.136
Jarque-Bera	0.223	0.0902	0.0460

Figure 7: Piecewise Regression Models for Mask Policy-related Tweets



4.2.3.2 Ridge Regression

The mask policy models had the lowest MSE (0.0013), meaning the piecewise ridge regression demonstrated strong prediction ability. The ridge regression Piece1 coefficients were consistently negative, indicating a decline in sentiment up to the stringency threshold. Piece2 for the 3-day lag was not estimatable given the high threshold (90.74), but Piece2 from the longer lag intervals indicated that after the breakpoint, sentiments decline more drastically. These findings are consistent with the initial regression results, showing a threshold relationship characterized by modest negative reactions at lower stringency, followed by increased negativity after reaching a stringency breakpoint. The date variable once again indicated that, regardless of the stringency, the public sentiment towards mask policies trended slightly upward over time.

Table 8: Ridge Regression: Mask Policies - All Locations

Lag Interval	Breakpoint	Alpha	MSE	Piece1 Coef	Piece2 Coef	Date_num Coef
3-day	90.74	10.0	0.0013	-0.00182	0	0.00014
7-day	71.58	10.0	0.0013	-0.00029	-0.00115	0.00013
14-day	71.58	10.0	0.0013	-0.00037	-0.00103	0.00013

4.3 Objective 3: City-Level Analysis

4.3.1 Lockdowns

Both Toronto and Ottawa exhibited negative sentiment changes in Piece1 across the lag intervals (Toronto: $\beta = -0.0012, -0.0011, -0.0010, p < 0.01$; Ottawa: $\beta = -0.0011, -0.0016, -0.0014, p < 0.044$). Given the high breakpoint for Toronto (90.74), there was no meaningful Piece2 data to investigate, meaning that Toronto showed a consistent downward trend in sentiment towards lockdown measures as policy stringency increased, without a breakpoint indicating a significant change in direction or severity of sentiment trends. Ottawa showed a slightly stronger initial drop in sentiment scores across all lags for Piece1 stringency

increases and did have a slightly positive shift in sentiment trends for Piece2 stringency increases. This positive change was the largest and statistically significant in the 7-day lag model ($\beta = 0.0094$, $p = 0.038$). Neither city model saw any notable results from the regression of the date variable, consistent with the general regression analysis suggesting that the progression of time did not have a significant impact on lockdown-related sentiments, regardless of policy stringency levels.

Table 9: Piecewise Regression Lockdowns by City

Metric	3-Day Toronto	7-Day Toronto	14-Day Toronto	3-Day Ottawa	7-Day Ottawa	14-Day Ottawa
Optimal Breakpoint	90.74	90.74	90.74	87.30	87.30	85.34
R-squared	0.054	0.044	0.038	0.025	0.034	0.027
Prob (F-statistic)	0.00356	0.0104	0.0191	0.166	0.0709	0.131
Piece1 Coefficient	-0.0012	-0.0011	-0.0010	-0.0014	-0.0016	-0.0014
Piece1 p-value	0.001	0.004	0.008	0.038	0.020	0.044
Piece2 Coefficient	3.095e-15	0	0	0.0065	0.0094	0.0055
Piece2 p-value	< 0.0001	0	0	0.156	0.038	0.066
Date_num coefficient	3.082e-06	1.072e-06	5.153e-06	-8.324e-05	-0.0001	-0.0001
Date_num p-value	0.959	0.986	0.934	0.372	0.250	0.223
Durbin Watson	1.546	1.535	1.517	1.595	1.592	1.585
Jarque-Bera	0.131	0.131	0.163	0.979	0.958	0.955

Ridge regression for Toronto showed slight negative trends in data prior to the breakpoint, and in line with the regression results, Piece2 coefficients were insignificant given the high breakpoints. The impact of the date variable is very small, suggesting that the impacts of the passage of time on sentiment scores is negative but very minimal.

In comparison, Ottawa's ridge regression also had negative Piece1 coefficients, illustrating negative sentiment trends prior to policies reaching the stringency breakpoints. Interestingly, Piece2 coefficients showed positive sentiment trends after the breakpoint, suggesting a possible, modest, threshold relationship. Ottawa also had a larger coefficient for the date variable, meaning that regardless of policy stringency, the sentiments of the public

towards lockdown policies were trending slightly downward over time. These results are similar to the overall trends, where lockdowns appeared to have the weakest relationship between stringency and sentiments. However, Ottawa did differ when isolated from the general dataset, showing a rebound in sentiments across all time lags after hitting the breakpoint.

Table 10: Piecewise Ridge Regression Lockdowns by City

City	Lag Interval	Breakpoint	Alpha	MSE	Piece1 Coef	Piece2 Coef	Date_num Coef
Toronto	3-day	90.74	10.0	0.0025	-0.00090	0	-0.00003
	7-day	90.74	10.0	0.0025	-0.00088	0	-0.00003
	14-day	90.74	10.0	0.0026	-0.00090	0	-0.00002
Ottawa	3-day	87.30	10.0	0.0066	-0.00078	0.00380	-0.00014
	7-day	87.30	10.0	0.0065	-0.00083	0.00388	-0.00014
	14-day	85.34	10.0	0.0066	-0.00093	0.00406	-0.00017

4.3.2 Vaccine Mandates

Results from the piecewise regression analysis for both cities in the vaccine mandate category is summarized in Table 11. For tweets originating in Toronto, the 3-day Piece1 changes were positive ($\beta = 0.0073$, $p=0.008$), followed by a sharp drop in sentiments in the 7-day model ($\beta = -0.0090$, $p=0.004$), and a slightly negative trend in the 14-day lag model ($\beta = -0.0015$, $p = 0.011$). In the 14-day model, the Piece2 coefficient did become slightly positive ($\beta = 0.0039$, $p=0.110$); however, along with the other lag models, the Piece2 results were not statistically significant.

Ottawa demonstrated a consistent response across all lags (Piece1 coefficients (β) ranging from -0.0126 to -0.0035 , all $p < 0.002$). After the breakpoint, the shorter intervals did not show meaningful effects ($p>0.05$), though, in the 14-day model Ottawa displayed a positive change in score ($\beta = 0.0052$, $p=0.005$). These results indicate that Toronto Twitter users showed initially positive responses to increases in policy to the breakpoint in the shortest lag, but in longer time intervals their reactions were negative; after hitting a

stringency breakpoint, the reactions did not show significant changes in sentiment score trends. Ottawa by comparison reacted more negatively across all time lags to policy stringency increases, with the strongest reaction in the 7-day lag. Though only significant in the 14-day lag model, there appeared to be a positive upward trend in Piece2 data, again suggesting a positive change in sentiment after the stringency breakpoint.

Table 11: Piecewise Regression Vaccine Mandates by City

Metric	3-Day Toronto	7-Day Toronto	14-Day Toronto	3-Day Ottawa	7-Day Ottawa	14-Day Ottawa
Optimal Breakpoint	68.14	68.14	85.34	68.14	68.14	80.42
R-squared	0.072	0.075	0.049	0.072	0.093	0.051
Prob (F-statistic)	0.00159	0.00114	0.0158	0.00149	0.000169	0.0138
Piece1 Coefficient	0.0073	-0.0090	-0.0015	-0.0126	-0.0159	-0.0035
Piece1 p-value	0.008	0.004	0.011	< 0.0001	< 0.0001	0.002
Piece2 Coefficient	-0.0005	-0.0004	0.0039	0.0004	0.0005	0.0052
Piece2 p-value	0.313	0.457	0.110	0.493	0.376	0.005
Date_num coefficient	0.0002	0.0002	0.0001	7.931e-05	0.0001	-4.572e-05
Date_num p-value	0.004	0.002	0.171	0.334	0.122	0.605
Durbin Watson	1.224	1.164	1.151	1.329	1.286	1.236
Jarque-Bera	1.42e-12	2.21e-12	8.51e-20	0.700	0.903	0.273

Ridge regression analysis reinforced the patterns seen in the piecewise regression analysis. Toronto and Ottawa both showed negative trends through all three Piece1 coefficients, with the 7-day lags being the most negative for both cities. Toronto's Piece2 coefficients more negative in the first two lag intervals compared to Ottawa, where all three were slightly positive. Both cities had positive coefficients in the 14-day lag model, showing a gradual rebound. Again, the date variable had a minor impact on the sentiment scores over time, being slightly more significant in the 3- and 7-day Toronto lags. Ottawa's 14-day date variable was slightly negative, suggesting that at the longer lag period, date begins to cause sentiments to trend slightly downwards, regardless of policy stringency. Ridge regression suggested that the response from Ottawa was less positive compared to the piecewise regression.

Table 12: Piecewise Ridge Regression Vaccine Mandates by City

City	Lag Interval	Breakpoint	Alpha	MSE	Piece1 Coef	Piece2 Coef	Date_num Coef
Toronto	3-day	68.14	10.0	0.0048	-0.00454	-0.00102	0.00013
	7-day	68.14	10.0	0.0049	-0.00761	-0.00094	0.00018
	14-day	85.34	10.0	0.0052	-0.00220	0.00608	0.00002
Ottawa	3-day	68.14	10.0	0.0047	-0.00815	-0.00044	0.00002
	7-day	68.14	10.0	0.0048	-0.01320	-0.00039	0.00009
	14-day	80.42	10.0	0.0053	-0.00448	0.00549	-0.00009

4.3.3 Mask Policies

In municipal comparisons from the regression results in Table 14, Piece1 coefficients for both cities were statistically insignificant with increases in stringency. Piece2 figures for Toronto showed significant negative trends in sentiments toward mask policies at all intervals as stringency increased, with the sharpest decline in sentiment scores being seen in the 3-day lag ($\beta = -0.0029$, $p=0.021$). As the lag grew to 7- and 14-days, the negative trend became somewhat weaker, but still significant (coefficients (β): -0.0028, -0.0015), indicating consistent negative sentiments across time lag periods. In Ottawa, Piece1 results were positive but statistically insignificant, and Piece2 data showed declines in sentiment scores, with the sharpest drop in sentiment in the 3-day lag model ($\beta = -0.0021$, $p=0.001$) remaining consistently negative across the lag models. The city-specific analysis suggested that reactions between the populations were similar, though Toronto demonstrated less consistency with severity of reactions with sentiment trends being more negative in the first two lags for Toronto, but Ottawa maintained a more consistent negative reaction across the three lags after the breakpoint.

Again, the date variable showed a very slight positive trend in sentiment. This suggests that regardless of policy stringency, the sentiments expressed towards masks trended slightly upwards over the progression of time.

Table 13: Piecewise Regression Mask Policies – By City

Metric	3-Day Toronto	7-Day Toronto	14-Day Toronto	3-Day Ottawa	7-Day Ottawa	14-Day Ottawa
Optimized Breakpoint	82.88	82.88	71.58	72.07	72.07	72.07
R-squared	0.096	0.05	0.072	0.099	0.080	0.078
Prob (F-statistic)	0.000120	0.00108	0.00154	8.58e-05	0.000699	0.0008311
Piece1 Coefficient	-0.0007	-0.0005	0.0009	0.0014	0.0016	0.0022
Piece1 p-value	0.154	0.320	0.465	0.399	0.322	0.174
Piece2 Coefficient	-0.0029	-0.0028	-0.0015	-0.0021	-0.0018	-0.0018
Piece2 p-value	0.021	0.026	0.001	0.001	0.005	0.004
Date_num coefficient	0.0002	0.0002	0.0001	0.0002	0.0002	0.0002
Date_num p-value	0.001	0.002	0.008	< 0.0001	< 0.0001	0.001
Durbin Watson	1.199	1.190	1.162	1.395	1.392	1.370
Jarque-Bera	0.0210	0.00776	0.00442	0.00334	0.00283	0.00201

The ridge regression for the mask policy data revealed an interesting difference between the responses of Twitter users in Ottawa compared to Toronto. Toronto users were slightly negative based on the Piece1 coefficients – all were negative, meaning that up to the breakpoint, sentiments trended downwards. Ottawa was positive before hitting the breakpoints, meaning that sentiments were trending up. After the breakpoint, Toronto became more negative across all three lag models. Ottawa also became negative, and more so compared to the Toronto coefficients, suggesting more variable and stronger reactions from Ottawa Twitter users. The date coefficients were positive for both cities, but stronger for Ottawa, meaning that over time, regardless of policy stringency, Ottawa sentiments were trending upwards more drastically.

Table 14: Piecewise Ridge Regression Mask Policies by City

City	Lag Interval	Breakpoint	Alpha	MSE	Piece1 Coef	Piece2 Coef	Date_num Coef
Toronto	3-day	82.88	10.0	0.0015	-0.00070	-0.00156	0.00013
	7-day	82.88	10.0	0.0016	-0.00052	-0.00121	0.00011
	14-day	71.58	10.0	0.0016	-0.00018	-0.00074	0.00009
Ottawa	3-day	72.07	10.0	0.0021	0.00116	-0.00166	0.00025
	7-day	72.07	10.0	0.0022	0.00111	-0.00129	0.00024
	14-day	72.07	10.0	0.0022	0.00102	-0.00112	0.00023

Comparing the city-level results, Ottawa appears to be more volatile with stronger initial reactions, but overall, more positive with a better ability to rebound over time. As seen in Figure 8, Ottawa's tweets were more positive on average for all policy categories. Figure 8 illustrates the temporal trends in the data. Toronto's reactions show fewer spikes in the sentiment scores over time. A clear example of this is visible in the lockdown line, which seems to remain quite stable around the 0 axis and within the neutral threshold, compared to Ottawa, which had notable jumps in positivity in mid-March, and apparent volatility in the lockdown line through June. Figure 9 also illustrates a clear trend in the data, with Ottawa consistently scoring higher average compound sentiment scores across the pandemic policy topics compared to Toronto.

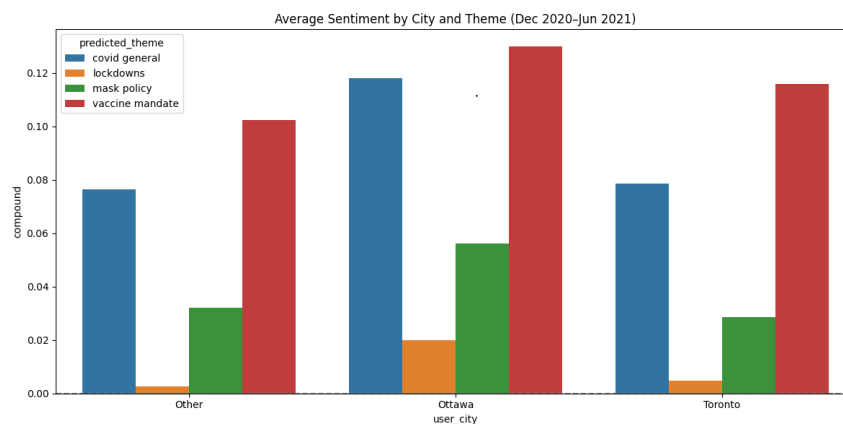
Figure 8: Average Sentiment Score Per Theme by City

Figure 9: 3-Day Rolling Sentiment Trends by City



Chapter 5: Discussion

This study uncovered nuanced patterns in public sentiment on Twitter in response to COVID-19 policy interventions within Ontario. By analyzing rolling sentiment trends alongside piecewise regression models, distinct emotional responses emerged across policy types, time lags, and increasing levels of policy strictness.

Lockdown sentiments were the least volatile, with average rolling sentiments remaining stable in and around the neutral threshold. Piecewise regression results showed no evidence of a threshold effect, with high breakpoint values and non-significant changes beyond them, suggesting that sentiment toward lockdowns was resistant to further deterioration regardless of policy escalation. Conversely, vaccine mandates were associated with the most positive sentiment trends over time. Interestingly, piecewise regression revealed that policy stringency was associated with improvements in sentiment, particularly in the longer lag models. This indicates growing public acceptance or perceived benefits as the mandates intensified.

Mask mandates displayed an opposite pattern. Initial sentiments were generally positive but mostly insignificant. Piecewise results revealed a significant decline in sentiment after crossing the stringency breakpoint. These findings suggest that while mask policies were initially well-received, they became increasingly controversial once perceived as overly intrusive. The time covariate exhibited varying levels of significance across models: sentiment toward mask and vaccine mandates showed modest improvements over time, whereas lockdown-related sentiment remained largely static.

5.1 Lockdowns

Lockdown-related compound sentiments consistently scored lower than tweet sentiments associated with other policy categories, with average compound scores mainly remaining in the neutral threshold (see Figures 2 and 8). Plotted over time, sentiment toward lockdowns exhibited minimal volatility compared to other categories. This is consistent with the findings

in prior literature, which identified the topic of lockdowns to be more moderately positive, and more stable compared to other pandemic-related topics (Tsao et al., 2022).

Visual sentiment declines observed in early April coincide with the major policy change of using the provincial “emergency brake” and the declaration of a province-wide state of emergency. Further drops occurred later in the month, coinciding with the implementation of further travel restrictions and closures. These temporal trends support the interpretation that prolonged lockdowns or pandemic measures contribute to dissatisfaction, and indicate pandemic fatigue (Evra & Mongrain, 2020, Pan et al., 2024, WHO, 2020b).

This sustained downward trend likely reflects emotional fatigue, resistance, or psychological distress rather than reactive spikes in sentiment tied strongly to policy stringency. Sukhwal and Kankanhalli, (2022) reported similar findings, with their research showing that lockdown sentiments generally began positively but reversed over time, even following the easing of restrictions. Factors like job security, income stability, mask mandates, and the challenges of social reintegration were driving concerns attributed to sustained low lockdown-related sentiment (Sukhwal and Kankanhalli, 2022).

Given that the lockdown models demonstrated the weakest statistical power ($R^2 = 0.057, 0.048, 0.053$), this persistent negative trend may stem more from broader public frustration or mistrust than from lockdown policy-specific features. Jalil et al., (2022), also observed initial public support for lockdowns during early government messaging, which waned as COVID-19 misinformation circulated. These patterns may be more reflective of an erosion of trust in public health measures stemming from prolonged exposure to misinformation and inconsistent messaging (Daas et al., 2024, Jalil et al., 2022; WHO, 2020b).

Piecewise regression confirmed consistent sentiment declines at all lag intervals, regardless of stringency. Significant Piece1 coefficients reflected immediate negative emotional responses, while non-significant Piece2 coefficients and the high breakpoints

(90.74, 85.34) suggest no cumulative negative backlash once strictness met the breakpoint level. Increasing policy stringency did not intensify negative sentiment in the regression models, indicating an absence of a threshold relationship. The model visualizations (Figure 5), appear to show an increase in sentiment in Piece2, though this is not statistically significant, again supporting a sustained negative sentiment towards lockdown policies, regardless of stringency (Sukhwal & Kankanhalli, 2022). The time trend being non-significant further implies that sentiment scores remained fairly static over time, irrespective of policy stringency factors (Daas et al., 2024, Sukhwal & Kankanhalli, 2022).

5.2 Vaccine Mandates

Throughout the study period, tweets related to vaccine mandates maintained the most positive sentiment, with 7-day rolling averages rarely falling below the neutral threshold (see Figure 3). This steady upward trajectory may reflect growing public trust in the efficacy of vaccines to protect against COVID-19, and acceptance of government vaccine mandates by the Twitter-using public (Lazarus et al., 2023). These trends are also in alignment with the studies conducted by Lavoie et al. (2022), and Pan et al. (2024) who found that the peak of vaccine hesitancy in Canada occurred in November of 2020. Given the analysis in the study began in December 2020, the upward trend is in line with this literature (Lavoie et al., 2022, Lazarus et al., 2023, Pan et al., 2024).

Regression results showed that, in contrast to the consistency of lockdown trends, vaccine mandates initially provoked resistance, especially seen in the 14-day lag. But sentiments revealed a statistically significant rebound (Piece2: $\beta = 0.046$, $p = 0.029$) after stringency reached the breakpoint. Ridge regression models also validated these observations, highlighting a negative response at low stringency levels, followed by a positive turn after the breakpoint. This relationship is consistent with the finding of Zhu et al. (2024), whose analysis of data from a national survey indicated that public support for vaccines was highest during periods of strict policy enforcement. Their findings suggest that strict vaccine policies may have signaled to the public government seriousness and urgency which improved levels of the perceived legitimacy and trustworthiness of the mandates (Zhu

et al., 2024). This is consistent with the findings of (Lazarus et al., 2023), where vaccine acceptance (neutral to positive sentiments) showed an increase in the 23-country study population, including a 26% increase in vaccine acceptance in Canada between 2020 and 2022 (Lazarus et al., 2023). As well as in the work by (Pan et al, 2024) who found sentiments towards vaccines were lowest in November 2020 and subsequently trended upward towards positivity. Ontario Twitter users in particular have been shown to have demonstrated a slight increase in support for government vaccine mandates over time, again reinforcing the findings that opinions towards vaccines became more positive over time (Pan et al., 2024).

The contrast in vaccine-related responses and lockdown responses may reflect differences in perceived intrusiveness and benefit as vaccine mandates were framed as protective and proactive, whereas lockdowns were often perceived as restrictive and reactive (Zhu et al., 2024). Research has shown that acceptance of vaccine mandates was driven not only by scientific messaging but also by community norms and a sense of civic duty (Lazarus et al., 2023, Zhu et al., 2024).

The significance of the time variable further suggests that the public sentiments towards vaccine mandates showed a trend of slight upward over time, regardless of policy stringency (Pan et al., 2024).

5.3 Mask Policies

The mask policy topic generated the highest volume of relevant tweets. This is consistent with the research of (Sukhwai & Kankanhalli, 2022), whose study found that in Facebook data, facemask-related concerns dominated the discourse on the platform throughout the first months of the pandemic, more than other topics like mental health and job insecurity, which fluctuated in relevance over time (Sukhwai & Kankanhalli, 2022).

Overall sentiment toward mask mandates remained in the neutral-to-positive range, though was more variable than vaccine-related tweets (see Figure 3). Notable sentiment dips in January coincided with increased restrictions, such as mandatory masking for school-aged children and recommendations for the use of masks outdoors. Mask policy sentiment may be

more sensitive to the perceived intrusiveness or shifting guidance based on these trends, and the research by Lee, Peng, et al. (2021) and Wismans et al. (2022).

Regression analysis revealed that mask-related sentiment exhibited the sharpest decline across policies. Mask policies demonstrated a clear threshold effect: Piece1 coefficients were mostly weak or non-significant, indicating minimal reactions to policies with weaker stringency. However, Piece2 coefficients were significantly negative across all lag intervals, revealing that sentiment deteriorated only after policy stringency surpassed a critical breakpoint. These findings were most pronounced in the 14-day lag, and supported by ridge regression, pointing to a delayed but substantial erosion in sentiment as mandate strictness intensified (Wismans et al., 2022).

Psychological Reactance is a phenomenon that describes resistance or hostility in response to perceived restrictions on personal autonomy (Steidl et al., 2015). Taylor & Asmundson (2021) suggested that psychological resistance to facemasks was a significant issue in Canada and was strongly motivated by public perceptions of inefficacy of masks, and an overexaggeration of the severity of the pandemic. The findings of a shift after a stringency threshold seems to support a potential point at which attitudes shifted to feel that the strictness of the mask measures were too restrictive for how effective the measure was, leading to increased reactance and negativity (Taylor & Asmundson, 2021).

The presence of significant time effects across all of the mask models suggests that the attitudinal shifts of the Ontario Twitter users were not solely driven by policy stringency, but also by other factors over time (Taylor & Asmundson, 2021). Interestingly, Sukhwai & Kankanhalli, (2022) saw mask-related sentiments rising over time, given this was in the earliest months of the pandemic, this difference in the sentiment trends may highlight the impact of pandemic fatigue or misinformation further into the pandemic (Krakowczyk et al., 2022, WHO, 2020b).

5.4 City-Level Analysis

City-level sentiment analysis revealed notable distinctions between the emotional responses of Twitter users in Toronto and Ottawa. Overall, tweets originating from Ottawa tended to be more positive across all policy categories, as illustrated in Figure 9. In contrast, Toronto's sentiment scores were more negative and aligned closely with those from the "Other" category, comprised of tweets without a specified city location. This discrepancy may reflect limitations inherent to Twitter's geotagging feature, which meant this study only captured and filtered users' location by those who explicitly marked their location. Given Toronto's larger population size, it is possible that Toronto residents were included in the "Other" category, potentially minimizing true city-level dynamics.

Figure 8 displays the rolling averages of daily compound sentiment scores across cities. Ottawa's graph again reveals more pronounced peaks and valleys, indicating heightened emotional reactivity to pandemic-related policy shifts compared to the steadier trend observed in Toronto. Such reactivity may be linked to greater community engagement or differing regional experiences with policy implementation and communication (Pan et al., 2024). Given the factors that have been found to impact mental health and pandemic experiences, it may be Ottawa's lower population density, higher mean income, and the increased access to green spaces that led to increased positivity in the city (Jenkins et al., 2022, Statistics Canada, 2023, Pan et al., 2024). Given that Ottawa is the nation's capital, it is also important to note that the federal government is the largest employer in the region (Twolan, 2023). As of 2020, over 120,000 people in the Ottawa region worked for Public Service Canada (Twolan, 2023). The job security and ability of many government jobs to transition to remote work during the pandemic, and the government hiring boom in the region from 2020-2022, likely also impacted the sentiments and experiences of pandemic policies in the region and may have contributed to the increased positivity compared to Toronto (Gatehouse & Leung, 2022).

5.5 Lockdowns

Toronto's responses to lockdown policies showed consistently negative sentiment across all lag intervals, with significant declines in each model. Each showing a statistically significant decline in sentiment scores. Piece2 data for Toronto could not be estimated due to the high breakpoint values (90.74), underscoring the absence of a measurable rebound in sentiment, or a further increase in the sentiment decline. In Ottawa, Piece1 coefficients similarly reflected a decline in sentiment, indicating initial disapproval. However, Ottawa users demonstrated a modest rebound in Piece2, particularly in the 7-day lag model, where the effect was statistically significant ($\beta = 0.0094$, $p = 0.038$). These findings suggest that while both populations expressed initial criticism toward lockdown policies, Ottawa users demonstrated greater emotional reactivity at lower levels of policy strictness, followed by signs of resilience as mandates intensified (Pan et al., 2024).

5.6 Vaccine Mandates

Sentiment toward vaccine mandates revealed a more complex pattern. In Toronto, sentiment was slightly positive at lower levels of policy strictness, but this effect reversed as mandates intensified. Across models reflecting increasing stringency, sentiment trended negatively, with later-stage coefficients remaining extremely small and statistically insignificant, implying no observable rebound in public opinion. Ottawa, by contrast, exhibited stronger initial emotional reactivity at lower stringency levels, followed by signs of recovery. The model's Piece2 coefficient under high stringency conditions was statistically significant, indicating a modest upward shift in sentiment as mandates became more stringent (Pan et al., 2024, Zhu et al., 2024).

Breakpoint comparisons further reinforced this interpretation: Ottawa's thresholds were consistently lower than Toronto's, suggesting that Ottawa users reacted to less strict changes in policy but were also more receptive to adaptation as mandates became firmly established. These results indicate that while Toronto users maintained steady skepticism,

Ottawa's sentiment trajectory reflected both emotional sensitivity and a greater capacity for long-term adjustment (Pan et al., 2024, Lazarus et al., 2023, Zhu et al., 2024).

5.7 Mask Policies

Between the cities, Toronto showed the most substantial sentiment decline at moderate levels of policy stringency, with statistically significant drops persisting as mandates became stricter. Ottawa mirrored this pattern, demonstrating similarly sharp sentiment declines across increasing levels of stringency, but with less variation across thresholds. Neither city exhibited evidence of emotional rebound beyond the breakpoint, implying that mask-related discontent may persist once triggered, and remained negative across all time lags.

The presence of significant and negative sentiment trends at higher stringency levels, and the significant time variable suggest that public attitudes improved gradually, irrespective of additional policy escalations but this time effect had to fight against sustained negative attitudes towards masks at high stringency. Considering these findings, mask mandates did not provoke significant immediate resistance, but the policies became increasingly controversial when perceived as overly restrictive (Lee, Peng, et al., 2021, Wismans et al., 2022). The consistent sentiment shifts across Piece2 values highlight the importance of stringency thresholds in shaping emotional responses among Twitter users in Ontario. However, the slight upward time trend indicates the potential for gradual normalization of these policies, maybe driven by habituation, or improved public communication (Pan et al., 2024).

5.8 Summary

Across all three policy domains, the 3-day lag models produced the strongest fits overall; this highlights the rapid temporal responsiveness of Twitter users. This also highlights how effective social media data can be in capturing public sentiment shifts in relation to public health crises and policy interventions quickly. Time emerged as a significant factor in sentiment scores for both vaccine mandates and mask policies, suggesting emotional recovery and adaptation over time. Lockdowns differed in this regard, with sentiment scores

being characterized by sustained negativity with a lack of evidence supporting temporal changes.

Policy stringency levels emerged as an important factor in influencing public sentiment. Piecewise regression highlighted breakpoints signifying thresholds at which sentiment trends would change their relationships with policy strictness. Though not pronounced for lockdowns, once the breakpoint stringency thresholds were surpassed for mask and vaccine-related measures, sentiments saw changes in public perception. Mask policy data appeared to highlight a point at which policies became too strict, and sentiments turned more negative. The vaccine data demonstrated a different pattern, with the response initially being more negative, and becoming more positive after policy strictness increased beyond the threshold, with a slight underlying sentiment improvement as time progressed.

5.9 Limitations and Mitigation Strategies

Given that this study uses social media data, the sample may not be representative of the general population of Ontario. As previously mentioned, it is nearly impossible to reliably extract accurate information about the demographics of social media users. This is due to privacy restrictions, as well as inconsistencies like whether users choose to input different pieces of information in the apps, along with whether the information is up to date, and if the user is being truthful. As of 2019, it was reported that there were 7.6 million active Canadian users on the Twitter platform (Bush, 2024). With almost half of these users checking the Twitter platform daily (Bush, 2024). Of Canadians under the age of 25 years old, 65% reported using the Twitter platform, along with 54% of those aged 25-34 years old (Bush, 2024). Older Canadians are less likely to use the platform, with only 27% of those over 55 using Twitter (Bush, 2024). Canadians have been shown to heavily depend on Twitter for information and discovery, and 64% of those aged 18-35 years old reported using Twitter to find and learn about trending news (Slater, 2018). While these results cannot fully be generalized to the population of Ontario, given the spread and popularity of the Twitter app at the time of the study, the data provides access to a large portion of the population, and can still provide useful insight into the general opinions of a large proportion of the population of

Ontario, especially the younger portions of the population. To handle this uncertainty, the interpretation of the results was handled carefully to ensure the results were not presented to be generalized for all of Ontario and can only truly be used to discuss the opinions of those on social media during the data collection period. This data cannot be used to make assumptions about the opinions or reactions from specific cultural, age, or gender-based groups.

This study leveraged Twitter data previously used for another study. For this reason, the keywords used to extract tweets from the Twitter API were not specifically chosen to target the policies of interest in this thesis specifically. Though the keywords used are expected to cover much of the same topics and likely pull the same tweets that keywords specific to this study would have covered, it is important to note that the predetermined keywords may have neglected to capture certain slang or policy-specific terms, potentially preventing some relevant tweets from being included in the dataset for analysis.

Along with usable demographic information being inaccessible through the Twitter platform, this study will only analyze tweets written in English. Excluding non-English posts results in the loss of differences in reactions and responses that may exist from different cultural groups, though, even if the research team was able to reliably analyze another language, VADER sentiment analysis is limited to English, meaning this methodology would not be able to accommodate tweets in any other language.

5.10 Significance

This study offered a novel examination of how policy stringency and timing influence public sentiments expressed on Twitter towards three major COVID-19 pandemic measures, lockdowns, vaccine mandates, and mask policies. Using large-scale Twitter data, and piecewise regression, the analysis of this research captured the trajectory changes of public opinions to real-time COVID policy changes. Usage of lagged models was particularly important for identifying delayed reactions, which can often be overlooked.

The breakpoint sensitivity seen with mask policies and vaccine mandates reveals that at least for some policies, there does appear to be a threshold effect on public sentiment. Beyond this threshold, there are marked shifts in the emotional tone expressed on Twitter. This supports the idea that the strictness of these policies determines the public response to them more than just the sheer existence of the policies. Moreover, the study identifies a pattern of adaptation over time, with certain policies showing emotional recovery while others (notably lockdowns) provoke sustained negativity. This thesis also identified distinctions in regional responses, with Toronto generally maintaining more negative sentiments, and Ottawa showing interesting increases in volatility, as well as increased positivity.

These observations have important implications for policymakers: they highlight the need for strategic timing, transparent communication, and emotional forecasting when implementing restrictive measures. Distinguishing differences in public sentiment responses to various pandemic policies, across time lags, and regionally contributes to the evolving literature on public health communication and the understanding of public behavioural responses during crises. This study demonstrated the utility of social media sentiment data as an indicator of a population's emotional climate. An understanding of public response can assist in improving the public health messaging of different policies and can identify measures that would benefit from more targeted messaging compared to others. Future research may be interested in performing similar analysis at larger levels, for example, on a national scale, to investigate potential differences in responses by province. Cross-platform analysis would also be useful to determine what different social media platforms capture, and how sentiments expressed by users on different platforms vary.

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Appendix A

Summary of Results

Intervention Category	Intervention Type	In Scope	Out of Scope	Research Category
Closures/openings	Closures/openings — daycares	Easing or tightening of restrictions of licensed and unlicensed child care centres (with noted extensions and exceptions for essential workers); seasonal day camp closures/openings are also included	N/A	Lockdowns
Closures/openings	Closures/openings — education	Opening and closures of schools (elementary, middle, secondary and post secondary); includes opening plans, measures implemented (e.g., mask wearing, distancing requirements and class sizes) and changes to learning options (e.g., mandatory in person, virtual or blended)	Infection control and outbreak measures in schools, including symptom screenings and testing (see Case management — education)	Lockdowns, Masks
Closures/openings	Closures/openings — health services	Easing or tightening of restrictions for non-essential and non-emergency health services offered in-person by regulated and unregulated health professionals Regulatory body directives announcing closures/openings of non-essential and non-emergency health services preceding a provincial/territorial government directive	Delay/resumption of elective and non-emergency medical procedures provided in acute or continuing care settings (see Health services — delayed/resumed medical procedures) Regulatory body directives announcing closures/openings of non-essential and non-emergency health services already captured in a provincial/territorial government directive	Lockdowns
Closures/openings	Closures/openings — non-essential services	Easing or tightening of restrictions to personal service establishments (e.g., hair, nails, tattoo), retail, food and drink services, and religious services determined non-essential (with noted extensions); in some cases, links to lists of essential services are included	Safety guidelines for essential businesses	Lockdowns
Closures/openings	Closures/openings — recreation	Easing or tightening of restrictions to entertainment businesses (e.g., theatres, bingo halls) and recreational services (e.g., libraries, museums, parks) and activities (e.g., fishing, hunting)	N/A	Lockdowns
Contextual Information	Contextual information — holiday	Holiday break dates for provinces/territories, including spring break and the winter holiday; a note is included to indicate if there are sub-provincial/ territorial differences	N/A	ALL

Distancing	Distancing — gatherings	Restrictions and easing of restrictions related to the number of people permitted in a gathering, the recommended distance for people to maintain and information on household bubbles	Capacity limits in businesses (see Openings and Closures)	Lockdowns
Distancing	Distancing — other	Distancing measures not captured by other intervention types (e.g., curfews)	N/A	Lockdowns
Distancing	Distancing — work from home	Recommendations and directives to facilitate working from home	Organizations that have implemented work from home policies independent of the federal and provincial/territorial recommendations or directives	Lockdowns
Financial and economic	Financial and economic — research and development	Federal investments to advance testing, treatment and vaccine research and development	Provincial/territorial investments to advance testing, treatment and vaccine research and development	Vaccines
Health services	Health services — equipment	Government management of critical goods such as personal protective equipment, hand sanitizer and ventilators (e.g., distribution of supplies, funding announcements related to procurement)	Announcements related to receiving ventilators or other critical equipment Guidance for the public to not use medical masks, as well as guidance for the public on wearing homemade masks (see Public information — masks)	Masks
Health workforce	Health workforce — safety guidelines	Safety guidelines for health professionals (e.g., provincial/territorial directives restricting movement of workers in different facilities, provincial/territorial directives regarding the use of PPE in health care settings, directives from regulatory bodies for safe openings)	N/A	Masks
Public information	Public information — masks	Recommendations or directives to wear masks as well as guidance on appropriate non-medical masks	Mask recommendations for school openings (see Openings — education)	Lockdowns
Public information	Public information — pandemic response plans	Releases of opening/closure plans with information on how services and businesses will resume/reduce operations	Updates to opening/closure plans Opening dates (see Openings category). School opening plans (see Openings — education)	Lockdowns
Public information	Public information — phase and alert level changes	Announcements of phase changes (including regional differences, where available); includes alert level systems implemented in fall 2020	Information on open/closed public places and services (see Openings and Closures categories)	Lockdowns
State of Emergency	State of emergency	Declarations and extensions of provincial/territorial states of emergency and public health emergencies related to COVID-19	Closures and restrictions to services (see Closures category)	Lockdowns
Travel	Travel — restrictions	Restrictions and easing of measures related to international and interprovincial/-territorial travel (e.g., initial federal travel advisories to certain countries; restrictions against non-essential	Regulations implemented by travel and tourism industries	Lockdowns

		travel, including border checkpoints); information on travel bubbles between jurisdictions		
Travel	Travel — self isolation	Self-isolation measures and directives for travellers (e.g., mandatory 14-day self-isolation for travellers, exceptions for travellers within travel bubbles or for other reasons)	N/A	Lockdowns
Vaccine	Vaccine — implementation plans and frameworks	Releases of vaccination implementation plans outlining information on phases and timelines as well as frameworks (e.g., ethical framework), key vaccination strategies (e.g., dosing intervals, pausing of vaccine administration) and provincial/territorial dashboards	Populations to be vaccinated (see Vaccine — population to be vaccinated)	Vaccines
Vaccine	Vaccine — other	Vaccine-related measures not captured by other intervention types (e.g., incentives for vaccination)	N/A	Vaccines
Vaccine	Vaccine — phase changes and milestones	Outlines key vaccination milestones firsts (e.g., first vaccination in jurisdiction for a population group)	Information on phases and timelines (see Vaccine — implementation plans and frameworks)	Vaccines
Vaccine	Vaccine — population to be vaccinated	Populations to be vaccinated as part of each phase of the implementation plan (e.g., seniors age 80 and older prioritized as part of first phase) or priority groups for vaccination if no phased plan exists; eligibility of the general population for vaccination as it is announced by age group(s) or other grouping (e.g., occupation, clinical risk factors)	Information on phases and timelines (see Vaccine — implementation plans and frameworks)	Vaccines
Vaccine	Vaccine — purchasing and allocation	First doses for specified vaccine(s) a province/territory received from the federal government; include the number of doses received if announced	Details around how the vaccine was administered or subsequent shipments of the same vaccine types Details on whom the vaccine was provided to (see Vaccine — population to be vaccinated)	Vaccines
Vaccine	Vaccine — regulatory approval	Regulatory approval of specified vaccine(s), including voluntary or regulatory recall	N/A	Vaccines
Vaccine	Vaccine — vaccination status	Includes vaccine passports or other approaches used to provide proof of vaccination and any relevant details	N/A	Vaccines

Appendix B

Stringency Index Coding Scheme

Measure	Coding
Restrict Public Gatherings	0 - no restrictions on gathering size 1 – restrictions on very large gatherings (above 500 people) 2 - restrictions on gatherings between 251–500 people 3 - restrictions on gatherings between 51-250 people 4 - restrictions on gatherings of 11–50 people or less 5 - restrictions on gatherings between 10 people or less 6 - restrictions on gatherings of 5 people or less 7 – gatherings with another household are not permitted
Masks in Public Spaces	0 – no restrictions 1 – mask–use is suggested, but not required 2 –mask–use is required in all indoor public spaces 3 – mask–use is required in all indoor spaces legally enforced 4 – mask–use is required in all indoor and outdoor spaces, legally enforced
Schools	0 – no restrictions (schools open) 1 – physical school buildings are open but with altered environments to reduce student movement (ie: dedicated class bubbles, staggered breaks) resulting in a significantly different learning environment 2 – some physical school buildings are closed, student schedules are altered with some learning moved to remote delivery 3 – all physical schools are closed and all learning has moved to remote delivery
Masks in Schools	0 – no restrictions 1 – mask–use is suggested, but not required 2 – mask–use is required for students (typically grades 4+) but not in all settings 3 – mask–use is required for students (typically grades 4+) in all settings
Care Homes	0 - no restrictions (in-person visitation permitted) 1 - in-person visitation is limited to a few essential caregivers 2 - in-person visitation is not permitted
Dining and Restaurants	0 – no restrictions (restaurants open) 1 – restaurant dining (indoor or outdoor) is open but with restricted capacity 2 – restaurant dining is closed indoors, but patios are open 3 – restaurants are only open for delivery, drive-thru and curbside pick up
Non-essential Retail Businesses (such as specialty stores and retailers)	0 – no restrictions (non–essential retail businesses open) 1 – partial closure or limited capacity of some non–essential retail businesses 2 – all non–essential retail businesses are closed
Non-essential services (such as salons, spas, and gyms)	0 – no restrictions (non–essential services open) 1 – partial closure or limited capacity of some non–essential services 2 – all non–essential services are closed
Cultural Services and Venues	0 – no restrictions (cultural services and venues open) 1 – partial closure or limited capacity of some cultural services and venues 2 – all cultural services and venues are closed

Intra-provincial Travel	0 – no restrictions (permit intra–provincial travel) 1– restrict intra–provincial travel
Inter-provincial Travel	0 – no restrictions (permit inter–provincial travel) 1– restrict inter–provincial travel
Curfew	0 - no curfew in place 1 - curfew in place
Immunization Record	0 - no restrictions (immunization records may be available, but provincial governments have not provided guidance or recommendation around use) 1 - Provincial governments have stated that providing proof of immunization or a recent (48-72 hour) negative coronavirus test is voluntary for individuals, and is at the discretion of businesses and some organizations 2 - Provincial governments have provided guidelines that require proof of immunization or a recent (48-72 hour) negative coronavirus test is required to access some businesses and organizations, excluding big box retail 3 - Provincial governments have provided guidelines that require proof of immunization or a recent (48-72 hour) negative coronavirus test is required to access most businesses and organizations, including big box retail
Mandatory Immunization: Healthcare Employees	0 - no restrictions 1- all eligible healthcare employees are required to be vaccinated, have a valid medical exemption, or are required to undertake regular testing 2- all eligible healthcare employees are required to be vaccinated or have a valid medical exemption
Mandatory Immunization: Long-term Care Workers	0 - no restrictions 1- all eligible long-term care workers are required to be vaccinated, have a valid medical exemption, or are required to undertake regular testing 2- all eligible long-term care workers are required to be vaccinated or have a valid medical exemption
Mandatory Immunization: Public Servants	0 - no restrictions 1- all eligible public servants are required to be vaccinated, have a valid medical exemption, or are required to undertake regular testing 2- all eligible public servants are required to be vaccinated or have a valid medical exemption
Mandatory Immunization: K-12 Employees	0 - no restrictions 1- all eligible K-12 school employees are required to be vaccinated, have a valid medical exemption, or are required to undertake regular testing 2- all eligible K-12 school employees are required to be vaccinated or have a valid medical exemption

Appendix C

Manual Validation

Validation results are detailed in the table below. The accuracy of the topic assignments was generally slightly higher than the sentiment score accuracy, though the mask topic accuracy was lower-than-average. This is consistent with previous modelling done using this dataset by Tsao et al., (2022), who had similar success with modelling the mask topic from this dataset. The model was not as proficient at distinguishing between the use of the work mask in reference to a face mask, and “mask” used as a verb. Generally, reductions in accuracy of the sentiment scores were linked to subtle sarcasm difficult to discern without a thorough background understanding of the contextual factors of the moment.

Topic	Topic Accuracy (%)	Sentiment Accuracy (%)
Lockdowns	86	81
Vaccine Mandates	93	72
Mask Policy	61	85
Average	80	79

Appendix D

Legend of Events Overlay for Figure 4

1. 2020-12-26: Commencement of provincewide lockdown
2. 2021-01-12: Mask use mandated indoors for grades 1 to 3, and outdoors for all students, with expanded testing and screening protocols
3. 2021-01-14: Provincial state of emergency declared
4. 2021-01-25: Elementary/secondary schools resumed in-person learning with testing, asymptomatic screening and mask mandate for grades 1 to 3 (7 regions) AND announced that the province will delay administering 2nd doses of Pfizer vaccines from 21 days to no more than 42 days
5. 2021-02-19: Provincial state of emergency expired
5. 2021-02-19: Provincial state of emergency expired
6. 2021-03-05: Extended period between 1st and 2nd doses of all approved COVID-19 vaccines to 4 months AND priority groups for Phase 2 of the vaccine plan updated
7. 2021-03-22: Gathering restrictions tightened across province
8. 2021-03-29: Vaccine eligibility expanded to individuals age 70+ (12 regions)
9. 2021-04-03: Emergency brake lockdown placed on all of Ontario
10. 2021-04-08: Provincial state of emergency declared
11. 2021-05-03: Vaccine eligibility expanded to individuals age 18+ in hot spots
12. 2021-05-06: Vaccine eligibility expanded to include individuals 50+
13. 2021-05-11: Administration of AstraZeneca 1st doses paused, 14. 2021-05-13: Vaccine eligibility expanded to include individuals age 40+
15. 2021-05-18: General population age 18+ eligible to book a vaccine
16. 2021-05-22: Roadmap to Reopen released: a 3-step plan to reopen the province
17. 2021-06-02: Ended province-wide stay-at-home order
18. 2021-06-09: Provincial state of emergency expired
19. 2021-06-30: Entered Step 2 of Roadmap to Reopen plan – some opening of retail and some allowance for outdoor gatherings restored

Appendix E

Monthly 3-Day Rolling Averages



Appendix F

Code Repository

To access the source code used for this research, access can be requested at the following GitHub repository:

Grigg, B. (2025). *Social media sentiment analysis codebase*. GitHub.
<https://github.com/bgrigg99/BG-COVID-Twitter-Analysis.git>