Identifying Corporate Responses to COVID19 Using Twitter and Web Analyses

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Contents

Abstract

The spread of COVID-19 across the globe has produced global and possibly persistent economic disruption. This study follows the design science research process and conducts qualitative and quantitative analysis to identify and investigate Canadian agri-food company responses to COVID-19. The results show the possibility of capturing companies' responses from web-based data, the breadth of responses, and the relationships between the communication of corporate responses and their reception among social media users. Divergences of regression results across different languages are also discussed in this paper. The findings will help academic researchers, business leaders and policymakers understand corporate responses and subsequent reactions better.

Keywords: Web Analysis, Twitter Analysis, COVID-19, Company Response

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1.Introduction

The spread of COVID-19 and the related responses among governments, businesses, and individuals have profoundly disrupted the economic and social environments of businesses. Beyond the immediate disruptions, it can be expected that the impacts will be noticeable over years to come, and that economic activity will be profoundly shaped by both the disruptions and the responses of businesses, governments and individuals, and that the resumption and re-imagination of economic activity will be accompanied by further waves of disruption. Further, although the initial COVID-19 disruption has been on a scale not seen in recent history, scientists suggest that disruptions on this scale will be more common in the future – whether due to pathogens, climate change, or societal dynamics. Thus, to develop resilience for individual businesses and entire regions and supply chains to face future disruptions, it is important for business leaders and policy developers to understand the breadth and diversity of corporate responses, their development over time, and public reactions.

In this current turbulent time, innovation has an imperative role to play in withstanding and recovering from the aftermath of the COVID-19 (Brem et al., 2021; Cheema-Fox et al., 2020; Gyimah, 2020; Heinonen & Strandvik, 2020; S. M. Lee & Trimi, 2021). Many researchers mentioned that COVID-19 is a catalyst for innovation and resilience (Cheema-Fox et al., 2020; Gyimah, 2020; Heinonen & Strandvik, 2020; S. M. Lee & Trimi, 2021). Companies adopted a broad range of measures, such as providing flexible work schedules, cashless payment, e-commerce, and diverting their operations to satisfy customers' needs, to be more resilient and innovative in the face of adversity (Brem et al., 2021; Cheema-Fox et al., 2020).

Many studies have shown that social media can play a critical role as a source of data for understanding public attitudes and behaviours during a crisis. Government measures, such as social distancing, have led to more social interactions moving online on social media platforms (Abd-Alrazaq et al., 2020). More and more companies are on the way of building a robust online presence to communicate and engage with customers, maintain their trust, and restore employees' morale and confidence. Platforms such as Twitter have become central to the technological and social infrastructure that allows people to stay connected even during crises (Chen et al., 2020). Recent studies have demonstrated that Twitter data can be mined to extract useful information that can help understand the effects caused by COVID-19 on companies and organizations and also provide information about public reactions (Doogan et al., 2020; Jain & Tirth, 2020). Thus, monitoring tweets could be valuable during and after COVID-19 pandemic as the situation and people's reactions are constantly changing during this unpredictable time (Abd-Alrazaq et al., 2020; Pranesh et al., 2020). Also, Twitter data analysis might play a crucial role in understanding companies' behaviour and response during (or to) the COVID-19 pandemic.

Despite the COVID-19 economic impact and Twitter analysis being studied by many researchers, there is little research on company level impact and identifying companies' responses from social media. Additional studies in this area have been suggested by many other researchers (Abd-Alrazaq et al., 2020; Chen et al., 2020; Doogan et al., 2020; Jain & Tirth, 2020; Medford et al., 2020; Ordun et al., 2020; Pranesh et al., 2020).

Based on the views mentioned above, this exploratory study utilizes web scraped data and Twitter data of Canadian agri-food companies to conduct qualitative and quantitative analysis to identify and investigate company responses to COVID-19 and relationships between corporate responses and their reception among social media users.

The rest of this thesis is organized as follows. The second section structures relevant literature by themes and concepts. Research gaps, research questions and hypotheses are listed in the following sections. The research design and methods are described in detail in the fifth section. Section 6 introduces the data collection procedure. The next section shows web analysis. Section 8 presents the Twitter data preparation steps and exploration results. Section 9 shows the companies' responses identified from tweets. Section 10 presents Twitter regression analysis. After the discussion section, section 12 highlights the limitation and future directions of the study. The last part provides conclusions.

2.Literature Review

2.1 COVID-19

2.1.1 Comparison with Other Disruptions

Most existing literature categorizes pandemics within the same category as natural disasters (Sheffi & Rice Jr, 2005). They are both Low-Likelihood, High-Impact disruptions that affect normal activities (Ambulkar et al., 2015; Chopra & Sodhi, 2014; Kleindorfer & Saad, 2009; Pettit et al., 2013). However, pandemic outbreaks should be distinctively characterized since they have unique features (Ivanov, 2020b). Due to its long-term disruption and unpredictable scaling, a pandemic tends to generate simultaneous and extreme shifts in demand, supply, and logistic operation (Ivanov, 2020b). The spread of the pandemic can be interconnected and cause widespread ripple effects, jointly harming many industries (Okumus & Karamustafa, 2005; Yang et al., 2020). This pandemic crisis starts small but scales rapidly and disperses over many regions (Ivanov, 2020b).

Past infectious diseases (SARS, MERS, Swine Flu, Ebola) can be lessons for COVID-19 (Ivanov, 2020b; Jordà et al., 2020). They remind us that such pandemics are a fact of life and can generate societal difficulties when they are not appropriately managed (Mora Cortez & Johnston, 2020). Despite sharing similarities from a medical perspective, the evidence suggests that the current pandemic is very different from those previously experienced in the speed at which the disease spread, and the scope of its influence (Aday & Aday, 2020; Donthu & Gustafsson, 2020; Esper, 2021; Gomez et al., 2020; Singh et al., 2020). COVID-19 began as a health issue, quickly becoming an economic issue and a policy challenge for governments throughout the world (Franco-riquelme & Ordieres-meré, 2020; Golan et al., 2020; Maithreyi Seetharaman & Jaclyn

Gallucci, 2020). This kind of global pandemic is the rarest type in recent human history and can be characterized as a black swan (Mora Cortez & Johnston, 2020; Verma & Gustafsson, 2020). COVID-19 and related measures generated a new normal for businesses and individuals and caused response challenges for international governments (Brammer et al., 2020). Fighting this pandemic requires an ongoing highly coordinated effort across regional and national jurisdictions, between government and health officials as well as ongoing communications with the general public (EY Global, 2020). There has been a need to redesign the work–processes for many industries, as well as to address consumer pessimism, and erosion of trust in global trade (Morgan et al., 2020).

2.1.2 Background: Digital Transition and a More Integrated World

This pandemic took place at a time of dynamic digital transitions (Vial, 2019) accompanied by profound socio-technical transitions (Geels, 2002). Given the potential of digital technologies to enable communication, the transactions and delivery of services, and to support the delivery of products as well as production planning and supply chain management, the COVID-19 disruptions have accelerated the digital transitions (Almeida et al., 2020). Responses by businesses, individuals, and governments have been deeply shaped by applying existing technologies, their recombination, and the development of new technologies and applications.

Compared with the past, the world is much more interconnected (EY Global, 2020). The global economic connections are growing deeper, broader, and more intricate (McKinsey, 2016). The current business environment has become more turbulent and is experiencing constant change. In today's digital age, changes are occurring at unprecedented rates of velocity and scale. The wave of mega-trends, such as globalization, technological advances, environmental concerns, demographics changes, urbanization, the global pandemic crisis, and other forces, is making the marketplace increasingly uncertain (Lee & Trimi, 2021). As the world becomes increasingly interconnected and interdependent, supply chains can improve their efficiency through optimization and diversification (Chopra & Sodhi, 2014; Golan et al., 2020). However, at the same time, the global context also exposes supply chain networks to disruptions of increased complexity and fragility (Golan et al., 2020; Ivanov et al., 2019a). Complex supply chains have become more vulnerable to severe disruptions (Ivanov & Dolgui, 2019, 2020a, 2020b). Being globalized in structures, the supply chains of many companies became prone to the pandemic outbreak (Ivanov et al., 2017, 2019a, 2019b, 2010; Ivanov & Dolgui, 2019, 2020a, 2020b). Especially during the digital era, Industry 4.0 increases the supply chain coordination complexity and uncertainty (Ivanov et al., 2019b).

2.2 Influence

2.2.1 Scope of Influence

The impact that COVID-19 has already inflicted is unprecedented (EY Global, 2020; Franco-riquelme & Ordieres-meré, 2020; Morgan et al., 2020; Shanthakumar et al., 2020). There remain many unknowns regarding the spread, duration and potential disruptions of COVID-19~~,~~ making it difficult to fully determine this pandemic's impacts and the right response measures (Ivanov, 2020b).

Governments imposed unprecedented restrictions upon their citizens, including border controls, travel bans, lockdowns, banning mass gathering, and enforcing social distance (EY Global, 2020; Shanthakumar et al., 2020). Since WWII, the world has not experienced such severe restrictions in economies worldwide (Pantano et al., 2020). These measures profoundly affected almost all aspects of global economic and social life as they threatened supply chains and logistics, and caused resources and workforce shortages and extreme price distortions (Brammer et al., 2020; Fairlie, 2020; Verma & Gustafsson, 2020). Some changes caused by this pandemic, such as consumer spending patterns, working arrangements, and business practices, are anticipated to continue (Kenney et al., 2020).

2.2.2 Challenges Facing Companies

The government response policies of many countries severely impacted several businesses unprecedently across industries (Ferrara, 2020; Larue, 2020; Verma & Gustafsson, 2020; Yang et al., 2020). Companies' normal operations, their anticipated growth trajectories as well as their survival have been adversely affected (Brammer et al., 2020; Verma & Gustafsson, 2020; Yang et al., 2020). There are a series of disruptions for companies, the main ones being failures throughout the supply chains, profoundly changed demand by customers, impacts on the availability or productivity of staff, and operation interruption.

Supply Chain and Operational Challenges All the processes and stages in the supply chain are intricately linked. A minor delay or failure will trigger the butterfly effect, leading to a significant loss of production and output (Adobor & McMullen, 2018; Apostolopoulos et al., 2021; Barichello, 2020; Black et al., 2020). The COVID-19 outbreak has tested supply chain resilience (Mollenkopf et al., 2020; Ordun et al., 2020; Zhao et al., 2020). The pandemic is having a clear impact on the supply chains of virtually all manufacturers, retailers, and wholesalers(Ivanov, 2020a, 2020b; Ivanov & Das, 2020). The spread of the virus and government policies have broken most transportation links and distribution mechanisms between suppliers, production facilities and customers (Kumar et al., 2020). As the world attempts to go through this challenging time, most companies are struggling to maintain a steady flow of essential goods and services. Companies are dealing with challenges of demand-supply mismatch, sustainable supply chain challenges, and challenges associated with building a resilient supply chain. Companies need to evaluate their supply chain strategies, supply chain designs, and supply chain dependencies to prepare to address unexpected disruptions (Sharma et al., 2020).

Companies are facing operation challenges, such as those related to employee and customer health and safety, workforce availability, cash flow, sales, and marketing. Companies have experienced a reduction in the supply of labour. Measures to constrain the disease by lockdowns and quarantines have led to further and more severe drops in capacity utilization. A dramatic and sudden loss of demand and revenue have severely affected companies ability to function and caused liquidity shortages (Donthu & Gustafsson, 2020; Fairlie, 2020; Kumar et al., 2020). Furthermore, supply chain disruptions have led to shortages of parts and intermediate goods. Many businesses have been forced to close, and the closures are permanent because of owners' inability to pay ongoing expenses and survive the shutdown (lockdown). The ongoing impact on small businesses around the world is likely to be severe. Small businesses, especially start-ups, have a more limited number of suppliers and have less resilience and flexibility in dealing with these shocks' costs (Fairlie, 2020; Kuckertz et al., 2020).

For the agri-food industry, labour shortage is a primary cause of disruptions to the supply chains. Seasonal temporary or seasonal employment is important in agriculture production, including planting, sorting, harvesting, processing, or transporting crops to markets. Under restrictive measures, workers are absent from work due to sickness and movement restrictions (Aday & Aday, 2020; Apostolopoulos et al., 2021). Food-processing plants that are labour intensive, such as meatpacking facilities and dairy processing plants, were forced to temporarily halt or reduce operations due to COVID-19 outbreaks within their workforces. Infection control is a significant problem because of workers' close working and living arrangements. Adopting prevention and precaution measures and equipment has increased production costs (Weersink et al., 2021). Taking the farming industry as an example, farm operations, especially fruit and vegetable production (Apostolopoulos et al., 2021; Mishra et al., 2021), horticulture and garden nurseries (Phillipson et al., 2020), depend on seasonal or migrant labours. Under restrictive measures, there was a decline in labour productivity, higher labour, operation and transportation costs, significant losses in income for farmers, food shortages, and changes in consumer need and prices for products. Some farmers were forced to destroy their products by burning or leaving them to spoil because of these obstacles (Fao, 2020; Goddard, 2020; Mussell et al., 2020; Phillipson et al., 2020; Savary et al., 2020; Singh et al., 2020; Weersink et al., 2021).

In response to the pandemic, some countries have made significant restrictions in the transportation of goods and even banned their own exports to protect supplies, for example, Vietnam stopped exporting rice, and Russia banned the export of grains. COVID-19 has driven up costs and increased the time it takes to ship goods internationally. For companies that rely substantially on importing inputs are more susceptible to disruptions. It is hard for these companies to obtain raw materials from suppliers and ensure the continuity of food flow(R. Dixon et al., 2020). They are experiencing massive loss because agriculture products were impossible to transfer due to governments restrictive measures (Ma et al., 2021). An alternative way is to obtain their raw materials from domestic markets. However, the domestic food supply was significantly disrupted by labour shortages, and disruption of distribution systems (Savary et al., 2020; Singh et al., 2020). For some sparsely populated countries, such as Canada, food supply chains tend to be long and heavily dependent on well-functioning, long-distance transportation systems. Transportation and distribution networks become vulnerable to disruptions due to labour shortages and movement restrictions, particularly long-haul trucking (Hobbs, 2020; Singh et al., 2020).

Customer Behaviour Changes Customer habits are repetitive consumer behaviours formed around regular patterns of daily activity such as commuting patterns, hobbies, preferences, and social behaviour (Mcknight, 2020; Pantano et al., 2020). COVID-19 has caused significant disruption to consumer habits because of the public health protection measures, such as working from home, restricting social behaviour and prohibiting non-essential travel. As these patterns change, so do customer habits (Pantano et al., 2020).

The restrictive measures also influence customers' risk perceptions. Risk perceptions play a key role in determining behaviours (Ferrer & Klein, 2015; Ivanov et al., 2019a). Risk perceptions can be shaped by several factors, such as risk communication on mass media, personal health conditions, and cultural background (H. Kim et al., 2016). Lockdown strategies lead to emergency purchasing situations (Samson & Voyer, 2014; Sharma et al., 2020). Miscommunicating on health-related information can also lead to widespread public panic (Yang et al., 2020). For example, many consumers engaged in stockpiling behaviours considering the fear of disruptions to food distribution systems (Goddard, 2020; Phillipson et al., 2020). In the early stages of the COVID-19 pandemic, some store shelves were temporarily emptied (Goddard, 2020; Mussell et al., 2020). Customers expressed unexpectedly high demand in some categories, especially for frozen and meat products (Aday & Aday, 2020; Goddard, 2020; Mussell et al., 2020). Even though government and food industry representatives quickly emphasized that there was enough food in the system, short-run panic buying behaviours became self-perpetuating. Especially with increased reliance on social media, panic buying became serious since social media spread anxiety about the COVID-19 outbreak (Abdelsalam et al., 2020; Aslam et al., 2018; Mao, 2020; Naeem, 2021). Social media used some hashtags, such as "#toilet-paper-gate" and "#toilet-paper-crisis", which indicate consumers' panic behaviour during the coronavirus pandemic (Barr, 2020; Mao, 2020; Taylor, 2020; Wilsom, 2020). The stories, pictures, and experiences that people have shared on Twitter and Facebook also increased panic buying among other consumers (Abdelsalam et al., 2020; Aslam et al., 2018; Barr, 2020; Mao, 2020; Taylor, 2020; Wilsom, 2020). According to Barr's (2020) report, many Twitter users in America shared pictures of the empty shelves in Costco supermarkets during the COVID-19 pandemic. As a result, more people-initiated stockpiling, which increased the pressure on supermarkets and suppliers around the world (Abdelsalam et al., 2020; Aslam et al., 2018; Naeem, 2021). For most products, panic buying is likely to be a short-run problem. The long-run demand driving effect on food supply chain will arise from the decline of consumer income, overall demand impacts and shifts across product categories (Hobbs, 2020). Consumers can be expected to become more price-sensitive, and the need for income elastic products to decline more sharply as consumers substitute away from more expensive items (Ben

Hassen et al., 2020; Deconinck et al., 2020; Loxton et al., 2020). This may affect the behaviour of retailers in product category management and contractual relationship with suppliers. As demand falls, retailers may squeeze the supply chain to improve cost-effectiveness, posing challenges for many food processors and suppliers (Hobbs, 2020).

Furthermore, customer behaviour changes could be profound and are not likely to end after the COVID-19 passes (Ferrara, 2020; Pantano et al., 2020). Especially, due to the lower accessibility of store premises, combined with consumers' higher health concerns, (Mckibbin et al., 2020; Mollenkopf et al., 2020), people have dramatically shifted their shopping behaviour to online purchases (Pantano et al., 2020). Also, there has been an immediate increase in demand for alternative distribution channels, such as home delivery and curbside pick-up (Bapuji et al., 2020; Pantano et al., 2020). Customers may wish to maintain these changes even when the emergency is over (EY Global, 2020; Martin & Classens, 2020; Mollenkopf et al., 2020; Pantano et al., 2020; Venuto, 2020; Yang et al., 2020). This means companies will have to operate in new ways to face shifts in customer demand.

2.2.3 Opportunities for Companies

History has shown that all crises create opportunities (Kumar et al., 2020). Taking advantage of the newly created opportunities can be a winning strategy (Morgan et al., 2020). Times of uncertainty can be an occasion for innovation, sustainable growth strategies, and a new commitment to society (Franco-riquelme & Ordieres-meré, 2020; Zheng et al., 2020). COVID-19 presents enormous opportunities to some companies (Franco-riquelme & Ordieres-meré, 2020; Karmaker et al., 2020). Innovation in the COVID-19 times is happening rapidly and in the most inspiring ways (Mention et al., 2020). Innovation will play a key role in recovering from the aftermath of the coronavirus (Chesbrough, 2020). Some companies are among the first to offer and deliver innovative responses. Some of them changed their product/service offerings, others altered their product distribution channels, and some pivoted along both dimensions. Their innovations have alleviated the effects of the crisis (Morgan et al., 2020).

The innovation opportunities for agri-food sector mainly happen in food safety, food security, and sustainability (Borsellino et al., 2020; Christiaensen et al., 2020; *EIT Food*, 2020; Galanakis et al., 2020, 2021; Kennedy et al., 2020; Rowan & Galanakis, 2020; Smith, 2020; Vaio et al., 2020; Wesana et al., 2019). There is a pressing focus on food security regionally and nationally to mitigate against challenges presented by the potential occurrence of future viral pandemics such as that caused by COVID-19 to protect vulnerable critical supply chains (Galanakis et al., 2020, 2021; Kennedy et al., 2020). Innovations such as smart and active packaging, advanced traceability systems, new biosecurity arrangements, the application of biopesticides to agriculture and industry 4.0 are expected to grow substantially in the new era (Galanakis et al., 2021; Kennedy et al., 2020; Rowan & Galanakis, 2020; Vaio et al., 2020). Under the trend of intensive sustainable food production systems (such as digitization, artificial intelligence, big data, and automation in smart agriculture), supply chain management will become more efficient and sustainable from agricultural production to processing, retail, and consumption (Galanakis et al., 2020, 2021). New technologies and innovations can protect consumers by ensuring the food and food supply chain's safety and reduce food loss and the environmental impact of the agri-food sector (Galanakis et al., 2021; Kennedy et al., 2020; Rowan & Galanakis, 2020; Vaio et al., 2020; Wesana et al., 2019).

2.3 Companies Responses to COVID-19

The COVID-19 emergency has encouraged companies to operate in newer and more resilient ways to face challenges (Bapuji et al., 2020; (Margherita & Heikkla, 2021; Verma & Gustafsson, 2020). To foster a resilient foundation for the future, firms need to change their priorities in response to challenges like real-time decision-making, workforce productivity, business continuity, and security risks (Ivanov, 2020a, 2020b).

Companies are an important part of the global management of this pandemic outbreak (Chen et al., 2020; Verma & Gustafsson, 2020). They ought to be integrated into the governmental health contingency plans developed by WHO and governments(Mackey et al., 2020). Companies are responsible for the provision of optimal prevention to protect their employees' health during their work (Verma & Gustafsson, 2020). Keeping social distances and changing work routines reduces disease transmission and providing flexible hours and work locations (work-from-home options) minimize exposure risk (Mollenkopf et al., 2020). Relevant responses include the implementation of workplace hygiene and disinfection measures, the publication of office layout and use rules, the sharing of norms for physical interaction and employee tracking, the assessing and reporting of customer mobility, the adoption of prevention measures across all customer touchpoints, limiting customer access, and changing buying or payment (contactless) process (Mollenkopf et al., 2020; Zheng et al., 2020; Margherita & Heikkilä, 2021). Also, the pandemic forced workplace operations to go virtual. Capabilities related to digitalization are likely a critical factor in a company's ability to transition its workforce to a remote environment and reach customers through online-enabled channels (R. Y. Kim, 2020).

Some responses show companies' social responsibility. Companies donate money and provide financial support, resources, and products (face masks, hand sanitizer, and ventilators) to fight the pandemic. Some of them provide dedicated shopping hours for vulnerable consumers(Mollenkopf et al., 2020; Zheng et al., 2020). They also coordinate with agencies and institutions and share best practices and organizational experience, which can be useful for the community(Margherita & Heikkilä, 2021).

2.4 Responses to COVID-19 Identified on Social Media

Pandemic outbreak and preventative measures implemented by national, state, and local governments have put tremendous strain on peoples' daily life activities (Chen et al., 2020; Coling, n.d.; Kabir & Madria, 2020; Pokharel, 2020; Zhao et al., 2020). Social distancing measures, travel bans, self-quarantines, and business closures forced people out of public spaces. Much of the social interactions about these phenomena now occur online on social media platforms, including their own websites, YouTube, Facebook, Twitter, etc. (Abd-Alrazaq et al., 2020; Zhao et al., 2020; Zheng et al., 2020). Individuals, organizations, and governments are using social media to communicate with each other on several issues relating to the COVID-19 pandemic (Abd-Alrazaq et al., 2020).

Many businesses are aware of the risk of losing customers permanently due to COVID-19 and are focusing on building a robust online footprint in support of their physical, community-based presence (Mcknight, 2020). The lack of service staff due to the mobility constraints and preventive protocols foster the need for online support (Mora Cortez & Johnston, 2020). Customers and suppliers in their need for information are reaching websites and social medias more often than before the crisis. Social media also contributes to bi-directional communication and share feelings through comments, reviews, posts, hashtags, emojis, etc. (Mora Cortez & Johnston, 2020; Pranesh et al., 2020). Using social media during the COVID-19 can be very effective, particularly to communicate general information about firm operations (e.g., working hours, suggested contacts) and events that can be of public interest (e.g., contributions to the state or society, donations, measures to protect employees, webinars) (Margherita & Heikkla, 2021; Mora Cortez & Johnston, 2020). Companies must continue to engage and communicate with customers through channels. Reinforcing customers' interests and alleviating their concerns are priorities (EY Global, 2020). Social media communication by companies can influence the impression they leave on investors and users (Franco-riquelme & Ordieres-meré, 2020). Robust communication strategies can maintain customer trust, restore employees' morale and confidence, and retain market stability (Clift & Court, 2020; EY Global, 2020; Yang et al., 2020).

2.5 Research with Social Media Data

As the conversations on social media platforms are continuously created, a tremendous amount of socially generated data is accumulated (Pranesh et al., 2020). Social media is now a popular source of data in understanding public concerns, attitudes, and sentiment, user behaviour, and disease transmission dynamics (Mackey et al., 2020). Therefore, it is paramount to analyze the social media data to understand companies' behaviour and response during the COVID-19 pandemic (Kabir & Madria, 2020).

Amongst social media platforms, Twitter has a well-documented Application Programming Interface (API) for accessing the data (tweets) available on its platform. Therefore, it has become a primary source for researchers to extract data. Twitter data have been proven useful for various analyses, such as predicting crimes, stock market trends, election results, disaster management, misinformation propagation, and monitoring the public health and reactions during disasters or crisis (e.g., hurricanes, floods, earthquakes, terrorist bombing, floods), and disease outbreaks

(Buntain et al., 2016; (Bondielli & Marcelloni, 2019; Bovet & Makse, 2019; Inuwa-Dutse et al., 2018; Hirata et al., 2018; Ivanov et al., 2019a; Kabir & Madria, 2019; Nagar et al., 2014; Remko, 2020; Sebastian et al., 2019; Southwell et al., 2019; Wang et al., 2019; Zou et al., 2019)(See Table A1 in Appendix).

2.5.1 Social Media and Crisis Events

During crises, most people tend to spend relatively more time on social media platforms than normal (Imran et al., 2015, 2020; Lamsal, 2020) and conversations on social media platforms are usually informal, such as sharing personal safety status, discussing news, sharing opinions on crisis response measures, and disseminating ground-level information (Castillo, 2016; Imran et al., 2015). Thus, social media data can be analyzed and processed to extract situational information that can be used to derive actionable intelligence for an effective crisis response with proper planning and implementation. First responders and decision-makers can utilize this situational information to develop strategies that will provide a more efficient response to the crisis (Carley et al., 2016; Castillo, 2016; Cheong & Lee, 2011; P. Earle et al., 2010; Imran et al., 2014, 2015, 2020, 2016; Kalyanam et al., 2016; Nguyen et al., 2017; Takahashi et al., 2015). Earlier works(Carley et al., 2016; Chatfield et al., 2013; Cheong & Lee, 2011; P. Earle et al., 2010; Takahashi et al., 2015) have shown that the tweets related to a specific crisis can provide better insights about the event. Crisis tweets data can be classified into various categories, such as community needs, volunteering efforts, loss of lives, and infrastructure damages. This information can be sent to the relevant department for further analysis. (Carley et al., 2016; Castillo, 2016; Chatfield et al., 2013; Cheong & Lee, 2011; P. Earle et al., 2010; Imran et al., 2013, 2014, 2015, 2020, 2016; Kalyanam et al., 2016; Nguyen et al., 2017; Takahashi et al., 2015). In addition, social media data can also be used to identify misinformation, such as crisis-related fake news and unverified rumors (Bondielli & Marcelloni, 2019; Bovet & Makse, 2019; Inuwa-Dutse et al., 2018).

2.5.2 Previous Pandemic Studies on Twitter Data

Previous pandemic studies on Twitter data mainly focus on public health, and there is no research about companies' responses to the best of my knowledge. Examining the use of Twitter for public health research has attracted a lot of scholars' interests. Sinnenberg et al. (2017) identified six main uses of Twitter for public health: analysis of shared content, surveillance of public health topics or diseases, public engagement, recruitment of research participants, Twitter-based public health interventions, and network analysis of Twitter users. Other studies analyzed Twitter data for sentiment analysis and the use of Twitter to propagate credible vaccine-related web pages (Abd-Alrazaq et al., 2020; Ferrara, 2020; Pokharel, 2020; Sinnenberg et al., 2017; Winet & Winet, 2021). In 2009, Eysenbach (2009) described the infodemiology and infoveillance concepts as a set of "public health informatics methods" to "analyze search, communication and publication behaviour on the Internet." Twitter has been used extensively for "infoveillance" approaches to assess past outbreaks such as H1N1, Zika virus, and the Ebola outbreak (Chew & Eysenbach, 2010; Fu et al., 2016; Young et al., 2018; Zsidisin & Wagner, 2010). Chew and Eysenbach (2010) applied this concept for a content analysis of H1N1 posts on Twitter. They analyzed disease-related trends, the origin of shared resources, and the sentiment expressed in swine flu tweets as posted via the platform. Hagen et al. (2018) propose a network analysis approach to identify several distinct communities and influential actors using Zika-related tweets. Liang et al. (2019) described the diffusion paths of Ebola-related messages and demonstrated that the broadcast model of one-to-many dissemination dominated the Ebola discussion on Twitter. Influential and hidden influential users played a key role in successfully disseminating Ebola-related messages.

2.5.3 COVID-19 Twitter Research

A massive amount of human-generated information being exchanged on Twitter during COVID-19, has attracted researchers to develop various ideas that involve the use of Twitter data in multiple ways. Most of the studies utilize keywords to conduct research (Abd-Alrazaq et al., 2020; Chen et al., 2020; Franco-riquelme & Ordieres-meré, 2020; Ho et al., 2015; Medford et al., 2020; Shanthakumar et al., 2020). Twitter analyses focus on topic model, sentiment analysis, social network, and geospatial analysis, and most of these analyses are intertwined. (Abd-Alrazaq et al., 2020; Aday & Aday, 2020; Adobor & McMullen, 2018; Banda et al., 2020; Chen et al., 2020; Franco-riquelme & Ordieres-meré, 2020; Jahanbin & Rahmanian, 2020; Medford et al., 2020; Ordun et al., 2020; Shanthakumar et al., 2020; Sharma et al., 2020)(See Table A2 in Appendix).

(1) Keywords Analysis

Some scholars filtered tweets and conducted analyses based on predefined keywords. Banda et al. (2020) utilized Twitter Stream API to collect tweets and filter them with different keywords, such as “coronavirus”, “2019ncov”, ”corona virus”. Schild et al. (2020) utilized keywords “china” and “chinese” to investigate the prevalence of several racial slurs targeted towards Chinese and Asian people and track the changes over time. Abd-Alrazaq et al. (2020) extracted the text and metadata using a set of predefined search terms (“corona,” “2019-nCov,” and “COVID-19”). They analyzed the collected tweets using word frequencies of single (unigrams) and double words (bigrams).

Some studies focus on gaining insights from the most common keywords after checking the word frequency. Singh et al. (2020) found that the dominant words across their data set focus on the global nature of the virus, words describing the virus and its spread, and responses to the outbreak. A strong focus on China reflects the focus of attention during the early phases of this epidemic. Franco-Riquelme and Ordieres-Meré (2020) looked for the most mentioned words related to the pandemic crisis and innovation and tried to understand how the message on innovation has changed. They observed three different phases of communication during the pandemic period. In the crisis's early stage, the companies have given mainly information to encourage calm and emphasize prevention. The second phase has a focus on adjusting to change and uncertainty. The third phase shows the recovery and the desire to start again.

Keywords analyses can also be conducted on hashtags. Chen et al. (2020) tracked the frequency of coronavirus-related hashtags, specifically those that contain the substrings “wuhan”, “coronavirus” and “covid”. They observed that the hashtag usage spikes when the WHO (World Health Organization) declared COVID-19 a global public health emergency and that the frequency of these hashtags changes with public announcements. Medford et al. (2020) extracted tweets matching hashtags related to COVID-19 and measure the frequency of keywords related to infection prevention practices, vaccination, and racial prejudice. Shanthakumar et al. (2020) grouped the hashtags into six main categories (General COVID, Quarantine, School Closures, Panic Buying, Lockdowns, and Frustration and Hope) to understand the chain of events and track the frequency of COVID-19-related hashtags over time quantitatively and qualitatively.

Related topics or themes can be obtained by keyword analysis and topic modeling. Ordun et al.(2020) extracted tweets containing thirteen single terms to gain insights about currently trending public concerns. The greatest rate of tweets occurred for the tweets consisting of the word "mask", followed by "hospital" and "vent". They found that people were discussing the issues around COVID-19 more frequently than symptoms and health conditions. They later found out that several themes consistent with these keyword findings are mentioned in topic modelling, including personal protective equipment (PPE) like ventilators and masks and healthcare workers like nurses and doctors.

(2) Topic Modeling

Latent Dirichlet Allocation (LDA) is a widely used topic modelling algorithm when researchers conduct topic modelling. Medford et al. (2020) iteratively trained multiple LDA models using different numbers of topics to maximize a topic coherence score. Ordun et al.(2020) used pattern matching and LDA to select twenty different topics on the spreading of coronavirus cases, healthcare workers, and personal protective equipment (PPE). Then, they generated graph visualizations of COVID-19 retweet cascades by applying machine learning methods, such as Uniform Manifold Approximation and Projection (UMAP) to visualize LDA. Abd-Alrazaq et al. (2020) used the LDA algorithm to find natural clusters in the language of the tweets and then combine the results with word clouds to summarize the topics and group associated terms.

After building topic models, scholars gain a better understanding of COVID-19 relevant topics on Twitter. Medford et al. (2020) found that the economic and political impact of the COVID-19 is the most commonly discussed topic, while public health risk and prevention is among the least discussed. Singh et al. (2020) identified eight high level categories: Economy, Emotion, Illness, Global Nature, Information Providers, Social, Government Response, and Individual Response. They also observed that most Twitter conversations are about one of two topics: either health or the virus itself or the global nature of the pandemic. Sharma et al. (2020) collected tweets from eighty-nine NASDAQ 100 firms, individual users, and twenty-six supply chain professionals to perform topic analysis. After that, they identify that firms are facing four challenges: demand-supply mismatch, technology, development of a resilient supply chain and construction of sustainable supply chain. Abd-Alrazaq et al. (2020) identified twelve topics, which were grouped into four main themes: origin of the virus; virus sources; virus impact on people, countries, and the economy; and ways of mitigating the risk of infection. Hosseini et al.(2020) listed the top topics as well as the top words associated with each topic. They found that the experience of living under home quarantine is the most dominant topic. Twitter users mostly complain about life under quarantine and talk about what they no longer can do due to restrictions. Some users also blame their fellow citizens for not taking the situation seriously. Man et al. (2020) employed several sets of topic modeling, with each set containing 5 to 10 topics. After reviewing the top 10 words from each topic, they developed different themes (health care environment, business economy, emotional support, social change, psychological stress) by consensus for each of the topics.

(3) Sentiment Analysis

Twitter is a rich medium that can be leveraged to understand the public sentiment in real-time and target public health messages based on user interest and emotion. To know public sentiments for different topics, researchers often conduct sentiment analysis and topic modelling together. Medford et al. (2020) found tweets with negative sentiment and emotion parallel the incidence of cases for the COVID-19 outbreak. Shanthakumar et al. (2020) performed a comparative sentiment analysis to understand the sentiment across the different hashtag groups. Their investigation reveals that people reacted positively to school closures and negatively to the lack of availability of essential goods due to panic buying. Abd-Alrazaq et al. (2020)found that the mean sentiment was positive for most topics and negative for two topics (deaths caused by COVID-19 and increased racism). The highest mean of positive sentiments was for the eating meat topic, followed by the wearing masks topic. The highest mean of negative sentiments was for “deaths caused by COVID-19” topic. According to Man et al. (2020)’s research, generally, the sentiments expressed in tweets were positive regarding the pandemic. This implies that the public remained hopeful in the face of an unprecedented public health crisis. They also created a heat map displaying the average sentiment score in every state in the US. Those states with lower infection rates tended to generate the most positive tweets, while states more directly affected by the pandemic were more likely to generate negative tweets. Strategies that engage the public and keep them hopeful are necessary for high-impact areas.

(4) Social Network Analysis

Social Network Analysis (SNA) is the process of exploring social structures via the networks and graph theory. The primary research of SNA on Twitter is investigating the key players and their influence. Ahmed et al. (2020) found that YouTube was the most linked information source by Twitter users. The most retweeted post belonged to a verified Twitter user, indicating that verified Twitter users may have had more influence on the platform. Yum (2020)’s study shows that demonstrates that public key players, such as the presidents, the WHO, the Centers for Disease Control (CDC), and news channels play a crucial role in the news of COVID-19 for people. This study also shows that topic-based networks and person-based networks play different roles in social networks.

Comparing different networks also attracted researchers' interests. Woo et al.(2020) used network analysis to investigate the information transmission networks and news-sharing behaviors regarding COVID-19 on Twitter in South Korea. The result suggested that the spread of information was faster in the Coronavirus network than in the other networks (Corona19, Shincheon, and Daegu). People who used the word "Coronavirus" communicated more frequently with each other.

Multiple studies have performed social network analysis on COVID-19 related hashtags. Lamsal (2020) conducted social network analysis using country, hashtag relations. The analysis confirmed the presence of 12 different communities within the dataset. Communities are formed based on the usage of similar hashtags. Also, a set of popular hashtags and their communities were identified. Gruzd and Mai (2020) examined the propagation of the #FilmYourHospital hashtag using social network analysis techniques to understand whether the hashtag virality was aided by bots or coordination among Twitter users. Another study (Wasim et al., 2020) collected tweets containing the #5GCoronavirus hashtag and performed network analysis to understand the drivers of the 5G COVID-19 conspiracy theory and strategies to deal with misinformation.

Social network analysis can also combined with topic modeling. Man et al.(2020) combined topic modeling with social network analysis. They created five social network graphs for five topics (health care environment, emotional support, business economy, social change, and psychological stress). They also found that among all five topics, the closeness centrality measure is the highest for emotional support, indicating that emotional support is the topic that is likely activated in each of the topic discussions.

(5) Geospatial Analysis

Geo-specific data can assist in surveillance purposes. Geospatial analysis results reflect the efficiency of using Twitter to monitor and track this pandemic infection. Jahanbin and Rahmanian (2020) found that geographical origins of tweets posted about COVID-19 are found to be consistent with the formal WHO report about incidence cases of COVID-19. Singh et al.(2020) looked at the relationship between where people tweet from, what locations people tweet about, and reported COVID-19 cases. Their results demonstrate strong correlations between location conversation mentions and confirmed cases. This suggests that social media conversations may be a leading indicator of disease cases, which can help inform the public about disease movement. If such messages are detected quite early, an efficient response can be targeted to that region (Lamsal, 2020).

(6) Results Evaluation and Validation

Most of the evaluation methods are checking samples, using manual works, or comparing manual results with automatic results generated by algorithms. Medford et al. (2020) analyzed the incidence of the tweets over time and manually reviewed a random 10% subset to validate content, evaluate narratives present, and explore examples of misinformation. Shanthakumar et al. (2020) developed a scalable seeded LDA topic modelling approach to automatically categorize and isolate tweets into hashtag groups and experimentally validate that their topic model provides a grouping like their manual grouping.

3.Gaps Identification in Literature

Due to the emerging nature of this research topic, there are still some gaps.

3.1 Lack of Specific Discussion about Company Level

The research of COVID-19 impact mainly focuses on economy, supply chains or industries, and is not specific to companies. Especially for the agri-food sector, most current research focuses on the challenges and opportunities brought by COVID-19 at the industry level. While there are a constantly increasing number of papers published on the COVID-19 influence topic since 2019, most studies on companies' responses remain reports or web pages. As such, there is little literature available for research on companies' responses to COVID-19.

3.2 Lack of Analyses on Companies' Twitter Data

Although many researchers have studied the role of Twitter during the COVID-19 pandemic, little is known about how different companies’ respond to COVID-19 on Twitter. Existing studies have tended to focus on the posting of responses from the general public. These studies do not distinguish the type of Twitter user (e.g., governments, health organizations, or the individual user). To the best of my knowledge, research conducted with companies’ tweets data is rare and most of the studies available analyze data over short periods with small samples. The twitter analyses available focused on investigating COVID-19 impact on companies or challenges companies are facing, and not companies' responses.

3.3 Lack of More Comprehensive Research

Most of the previous research employs the Twitter API to collect data. However, due to Twitter standard search API limits, most of the research on COVID-19 tweets used defined short-periods of data. Thus, findings may not be comprehensive. In addition, most of the studies only analyzed tweets in one language (mostly in English), limiting the generalizability of the findings of this worldwide outbreak. Finally, there are limited studies investigating companies' responses using more than one social media data.

4.Research Questions

This paper contributes to the literature emerging on COVID-19 by addressing the following research questions (RQ):

RQ1: What are the responses companies display in reaction to the COVID-19 disruptions?

RQ2: What are the relationships between the communication of corporate responses and their reception among social media users?

5.Research Design & Methods

5.1 Measurement Process (Operationalization)

RQ1: What are the responses companies display in reaction to the COVID-19 disruptions?

H1: There will be several response topics, such as hygiene measures, social responsibility, operation measures, etc.

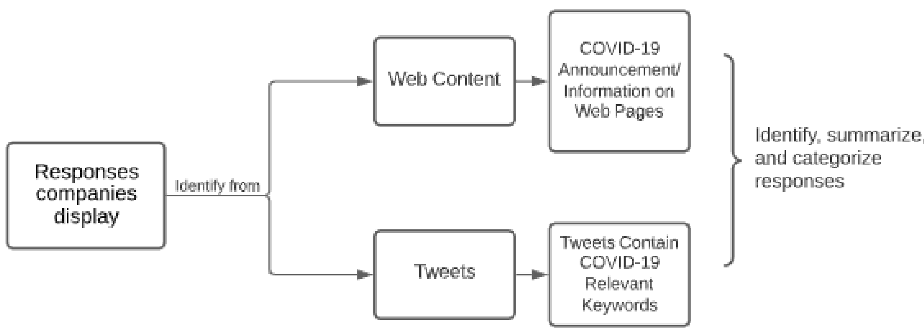


Figure 1 Operationalizing RQ1

Source: author's creation

RQ2: What are the relationships between the communication of corporate responses and their reception among social media users?

H2: There will be more interactions (likes) when the responses express more concern for employees, consumers and communities.

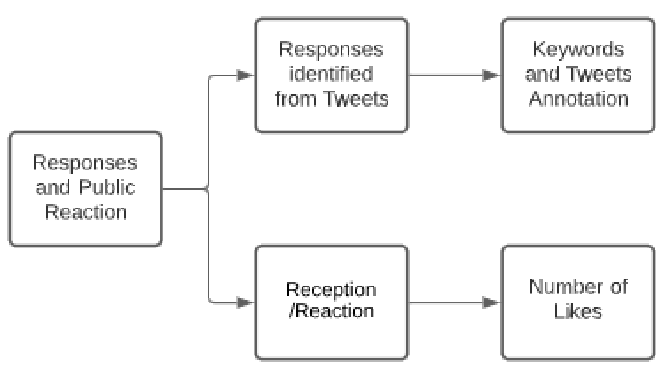


Figure 2 Operationalizing RQ2

Source: author's creation

5.2 Research Strategy and Process

This research falls into Design Science Research. The research process follows Design Science Research Methodology (DSRM) process model (Peffers et al., 2007), which consist of six activities in a nominal sequence, as shown in Figure 3.

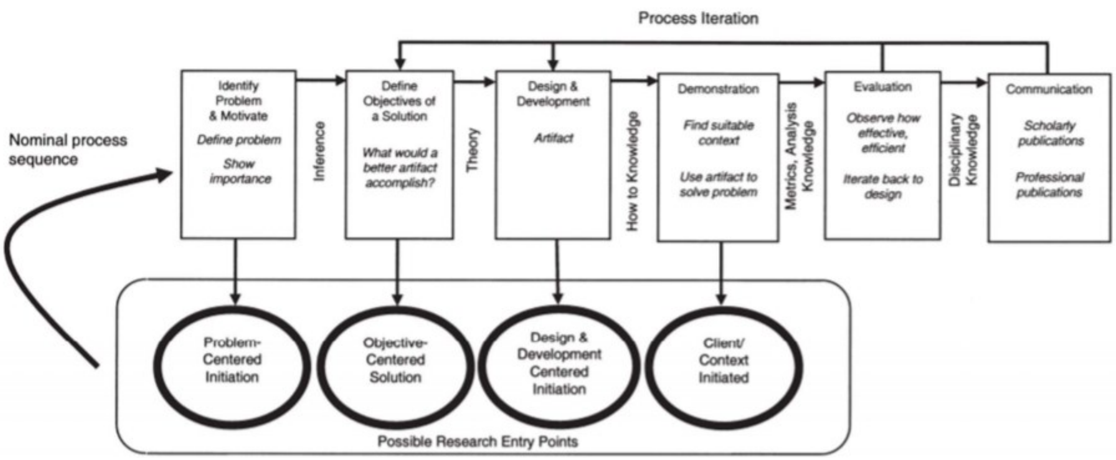


Figure 3 DSRM Process Model

Source: This image was from Design Science Research Methodology (DSRM) process model developed by Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

(1) Problem Identification and motivation

Even though the COVID-19 economic impact and Twitter analysis being studied by many researchers, a more comprehensive study that utilizes companies' web and Twitter data is needed due to the lack of specific discussion about company level and analyses on companies' web and Twitter data (Abd-Alrazaq et al., 2020; Chen et al., 2020; Doogan et al., 2020; Jain & Tirth, 2020; Medford et al., 2020; Ordun et al., 2020; Pranesh et al., 2020).

(2) Definition of objectives of a solution

This paper aims to find practical solutions that can identify companies' responses to COVID-19 and public reactions to these responses. The methods and results of the work presented in this study will be of value to researchers and businesses and policy developers.

(3) Design and development of artifacts/solutions

I designed artifacts that meet the objectives of this research. In this stage, the data mining process follows some steps of Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology (See Table B1 in Appendix B). When dealing with the qualitative data, I conducted Conventional (Emergent) Content Analysis and Directed Content Analysis. The detailed steps are discussed in the following sections.

These artifacts (Table 1) are shown as follows. They were produced through multiple iterations of development. These artifacts were developed based on my research questions and I explained how these artifacts provide solutions to these research questions in the following sections.

Table 1 Artifacts

Artifacts	Explanation
Constructs	COVID-19 keywords, COVID-19 topics, companies responses categories/patterns
Models	This research will show COVID-19 impact on companies' social communication and the relationships of different variables
Methods	Develop methods to capture the broad range of corporate responses by analyzing web-based, non-survey data

Source: created by author following Design Science Research method

(4) Demonstration
The method and research results will be presented in this study and the hypotheses will be tested by using the artifacts.

(5) Evaluation
To observe how efficient and effective the proposed artifacts are in solving the research questions, I employed descriptive and analytical evaluation methods to show the artifacts' utility and effectiveness. This study has two analysis parts: web, and Twitter. The results generated from these two aspect analyses can also be used to compare and complement each other to get all-around results. There are several iterative procedures to ensure the validity and reliability of the outcome. I integrated topic model results, manual checking results, official documents, available literature, and professional suggestions from supervisor and other researchers to avoid bias and be rigorous in analyzing the data.

(6) Communication
I presented the research method and part of the results to other scholars and students in Policies, Processes and Practices for Performance of Innovation Ecosystems Virtual Conference on May 12, 2021. In addition, results are expected to be used on a digital platform for the Food and Beverage sector.

5.3 Research Process Overview

This paper utilized both qualitative and quantitative methodologies to integrate different perspectives. The qualitative analysis aims to identify companies' responses categories and corresponding keywords to prepare for quantitative analysis. This research is a mixed-methods study and includes both inductive and deductive processes. I conducted Conventional (Emergent)

Content Analysis and Directed Content Analysis when identifying and summarizing the responses categories and keywords list (Figure 4).

The analysis of this research has two parts, web analysis and Twitter analysis. Conventional content analysis is the initial approach that I used to identify the responses categories and relevant keywords. At that time, conventional content analysis is an appropriate method since there are limited studies (Hsieh & Shannon, 2005) on this research topic. Most of the references that I can find are blogs, online discussions, and consulting companies' reports. I conducted web analysis using web scraped data. After importing web content in Nvivo, I checked the word frequency and word tree. In the process, I made notes of any patterns, thoughts, and initial understandings and highlighted some specific words from the information that seem to display companies' responses. After several round iterations, I identified some responses and summarized them into different categories.

Analysis on web content has some limitations due to the uncertain website update time and non-traceability of web data. To obtain more information, I conducted Twitter analysis. Since tweets can be downloaded retroactively, this research focuses more on the Twitter analysis part.

Another qualitative method I used is directed content analysis. The main themes and keywords identified from web analysis results were used as the initial keywords list for Twitter analysis. I used web analysis results to develop the initial coding scheme prior to beginning to analyze the Twitter data. I also consulted some previous research, including literature, reports, and official government documents to enrich and modify the initial keywords list (developed in web part) for tweets annotation.

Some keywords and topics were identified from Twitter data exploration results (topic modelling and unigrams, bigrams). As the tweets annotation proceeded, I manually checked unlabeled tweets to see if any relevant keywords were missing. Based on the checking results, I revised and refined the keywords and their categories.

After several adjustments, the responses categories and the final keywords list were finalized. After finishing the annotation with the keywords list, in order to answer RQ2, I conducted regression analysis to investigate the relationships between likes count and companies' responses.
The research process and methods are shown in Table 2.

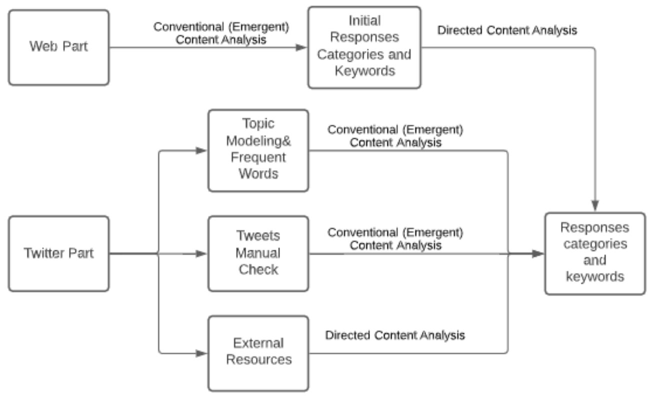


Figure 4 Qualitative Analysis Process

Source: created by author

Table 2 Brief Summary of Research Methods

Parts	Steps	Concrete Operations	Research questions that can be answered
1	Web scraping	• Develop COVID-19 dictionaries • Scraping the list of URLs	Partial RQ1: What are the responses companies display in reaction to the COVID-19 disruptions?
	Web content analysis	• Import into Nvivo • Checking word frequency, word tree and word cloud • Compile and categorize a comprehensive list of company responses	
	Validation	• Web data validation	
	Keywords	• Improve the keywords dictionary • Prepare for further research	
2	Twitter scraping	• Utilize Twint package to scrape tweets and profile data	Partial RQ1: What are the responses companies display in reaction to the COVID-19 disruptions? RQ2: What are the relationships between the communication of corporate responses and their reception among social media users?
	Data preparation	• Translate French Tweets • First Round Clean: Remove numbers, URLs, mentions and reserved words (RT, FAV) • Sentiment Score • Second Round Clean: Remove punctuations, emojis, emoticons, and convert uppercase characters to lowercase • Tokenization and Lemmatization • Filter out irrelevant data	

	Twitter Data Exploration	• Temporal Frequency • Top hashtags • Sentiment analysis • Word/Phrases Frequency • Usernames tweeting about COVID • Topic Modeling	
	Keywords list and Tweets Annotation	• Enrich keywords list (external resources, manual check) • Label tweets based on keywords	
	Statistical Analysis	• Create variables • Factor analysis • Cross Tabulation • Conduct statistical analysis	
	Evaluation	• Model Selection • Models Evaluation • Robustness Check	

Source: created by author

6.Data Collection

6.1 Data Collection Procedures

This paper analyzed data from two different sources, websites and tweets of Canadian companies in the agri-food sector, such as food and beverage production companies, agriculture service companies, and agriculture research organizations (See Figure C1in Appendix C). I collected both qualitative and quantitative data. For website data, I used a web scraper written in python to scrape the web content and social media accounts. As for the Twitter data, I used Twint to scrape tweets data, including id, username, retweet, hashtags, mentions, tweets, language, created time, likes count, retweet count, etc. Twitter profile data, including location, bio, username, number of following and followers, were also be collected (Figure 5).

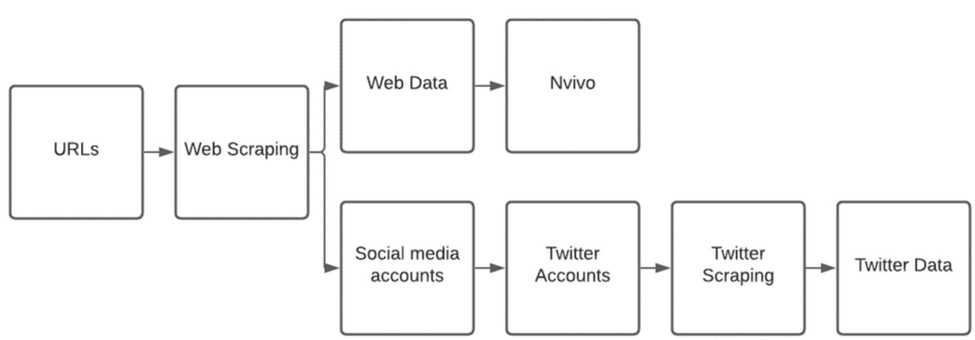


Figure 5 Data Collection Steps

Source: created by author

6.2 Web Content Data

This study respects the anti-scraper settings companies' websites. I set proper timeout and proxy agent settings to avoid being blocked. To collect enough data within a certain period, I selected an appropriate depth limit when scraping the website (Fan, 2018; Kaiying et al., 2020; Mitchell, 2018).

Stieglitz et al. (2018) mention the challenges when collecting social media data from a big data perspective(the four V's: volume, velocity, variety, and veracity). They note that the choice of an appropriate software architecture becomes essential in the collection phase. One proposed solution for storing and processing large amounts of social media data is to use NoSQL. According to the suggestion, I used MongoDB (NoSQL database) to keep the web scraped data.

In this step, I created the COVID-19 dictionary (Dictionary 1) first, and used this dictionary to scrape the web sites. After scraping, web content, word occurrence count, social media accounts were extracted and stored in MongoDB. There are 3811 full-text websites of companies were scraped. I then sorted the records by the number of these COVID-19 keywords occurrence.

6.3 Social Media Accounts Data

1331 companies have social media accounts. From the figures below, we can see that most of them have three social media accounts (Figure 6). Twitter, Facebook, Instagram are typical social media platforms used by these companies (Figure 7).

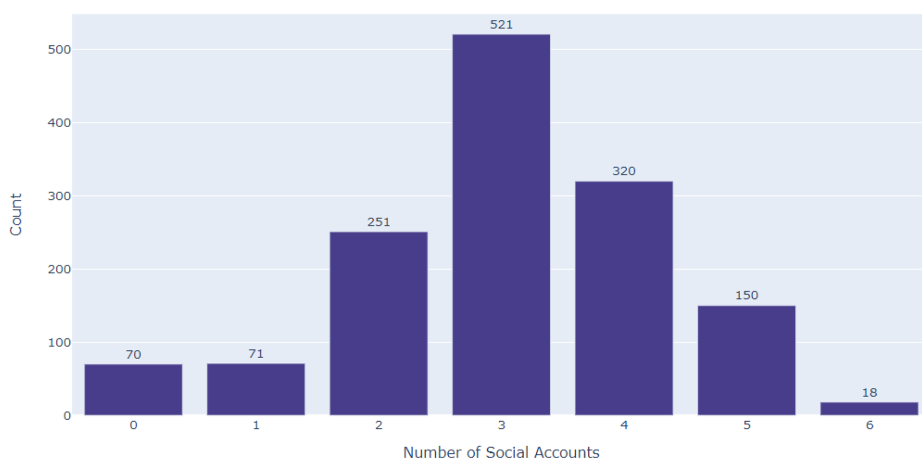


Figure 6 Number of Social Media Accounts

Source: created by author based on social media accounts data

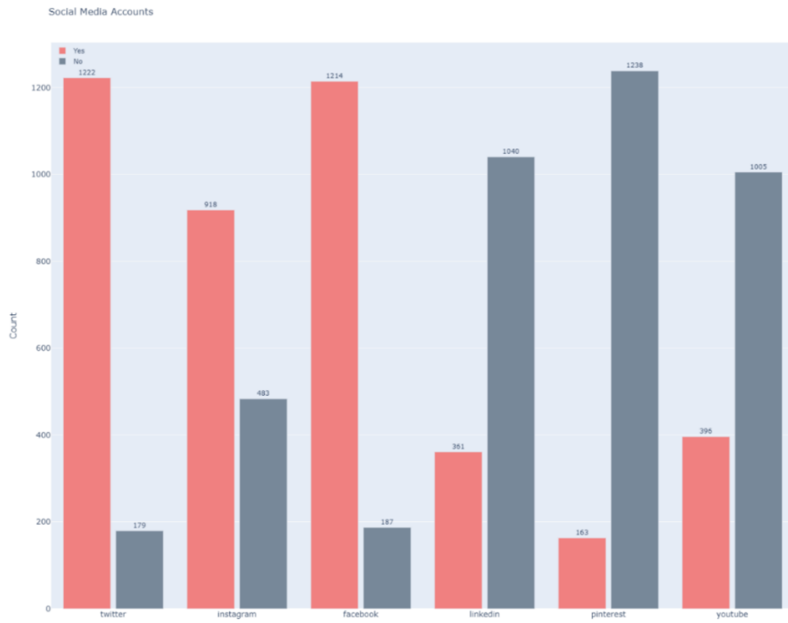


Figure 7 Companies Social Media Usage

Source: created by author based on social media accounts data

6.4 Twitter Data

I utilized python package "Twint" to scrape tweets companies posted in 2020 and Twitter accounts profiles data. The Tweets data set includes original tweets, replies to public user and retweets (See Figure C2, C3, C4 and Table C1, C2, C3 in Appendix C). Profile data set (See Figure C5 in Appendix C) contains username, bio, location, URL, join date, following, followers, total number of tweets etc. information.

I collected 1,292 Twitter accounts after doing the web scraping. After finishing scraping with these Twitter accounts, I had 273,165 tweets for 2020 (January to December). Some tweets' language codes are "und" (Undetermined), which may affect further analysis. Thus, I excluded those data and only considered English tweets and French Tweets.

Table 3 Summary of Twitter Data

Data	Number of Tweets
2020 Tweets	273,165
2020 English Tweets	252,640
2020 French Tweets	10,567
Twitter Accounts Profile	1,292

Source: created by author based on Twitter data

Table 4 Number of Companies Tweeting in Different Languages

Language	Username Count (All Tweets)
English and French	207
Only English	754
Only French	12

Source: created by author based on Twitter data

7. Web Analysis

7.1 Web Analysis

I selected a sample of 14 companies with COVID-19 related posts on their websites from the database of 3811 full-text websites of companies in the agri-food sector. Using inductive qualitative analysis and Nvivo, I compiled and categorized a comprehensive list of company responses (Figure 8). To validate my approach and ensure saturation, I compared the results with a Statistics Canada survey (https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3310023001) on company responses. I found that some companies' responses that might be expected on websites were captured. A small number of responses or events, such as postponing a merger or acquisition, were not captured, but they are unlikely to appear on websites (Table 5).

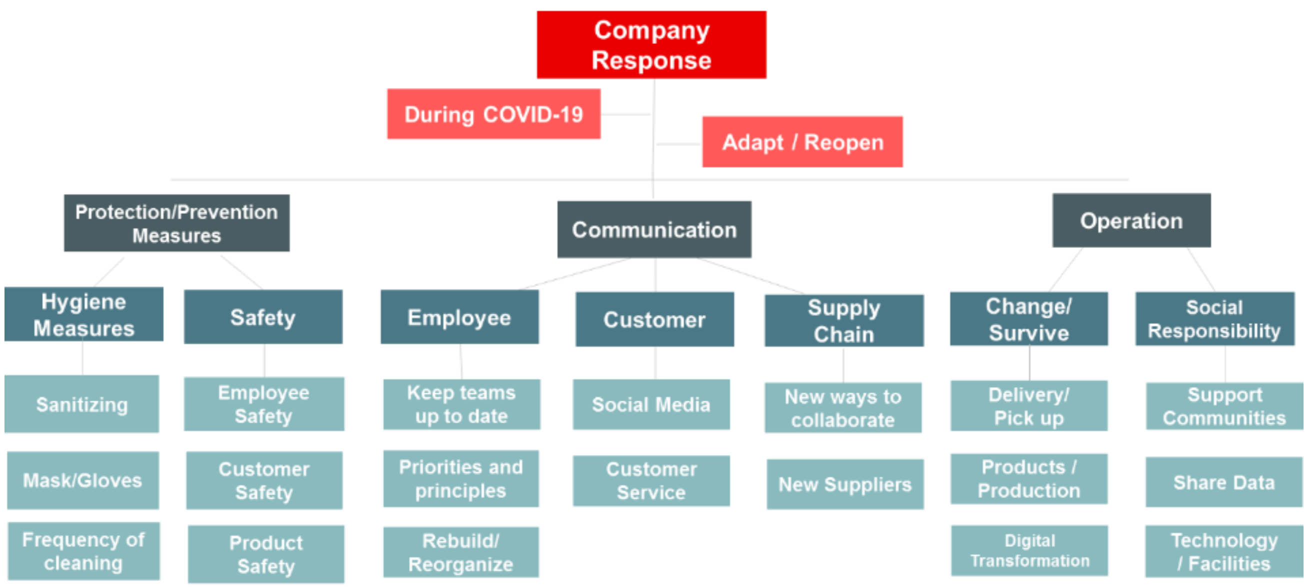


Figure 8 Company Responses Identified from Web Content

Source: created by author based on web content data

Table 5 Comparison with Statistics Canada Survey

Web Analysis	Statistics Canada survey
Covered	• Altered methods of production • Altered products or services offered to customers • Altered research and development • Discontinued a product or service • Added new ways to interact with or sell to customers • Increased use of virtual connections internally • Increased use of virtual connections externally or e-commerce • Voluntarily closed temporarily • Closed temporarily as mandated by government • Closed permanently • Invested in equipment to produce new products or expand existing product lines • Other changes made to adapt to COVID-19 situation
Not covered	• Postponed a merger or acquisition • Temporarily halted exports • Cancelled contracts • Increased/ Decreased maintenance costs

Source: created by author based on web content data and Statistics Canada survey. Survey link: https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3310023001

7.2 Improve COVID-19 Keywords Dictionary

The process of getting COVID-19 keywords is iterative (Figure 9). After several cycles, I added more words into Dictionary 1. In tweets analysis step, I took some words (COVID-19 synonyms, such as COVID, virus, pandemic, coronavirus) in Dictionary 1 as the initial dictionary to filter and extract COVID-19 relevant tweets. Some other words, such as delivery and online order, were supplement for tweets annotation keywords list.

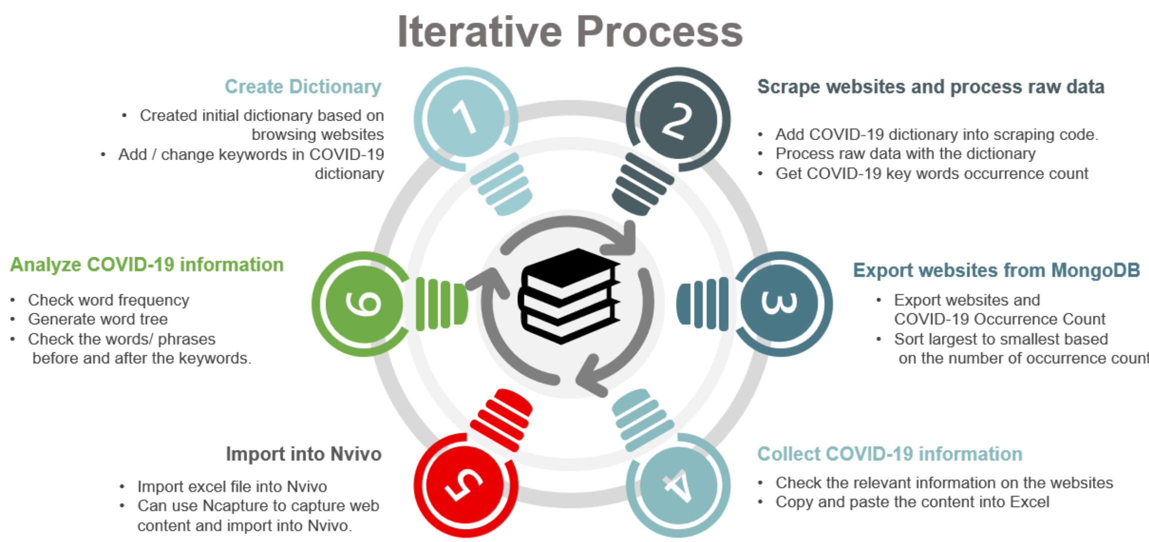


Figure 9 Keywords Dictionary Development Process

Source: created by author

8. Twitter Data Preparation and Exploration

8.1 Data Preparation

The data preparation and cleaning steps are shown as follows (Figure 10).

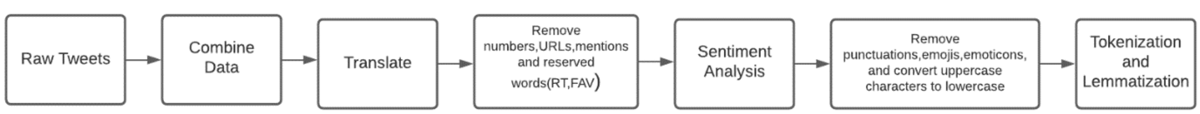


Figure 10 Tweets Data Preparation Process

Source: created by author

8.1.1 Data Combination and Tweets Translation

I combined tweets, profile, and social media account data sets based on Twitter usernames or URLs. After combination, I used the Googletrans python package to translate French tweets into English (See Table D1 in Appendix D).

8.1.2 Tweets First Round Clean

Most Twitter studies follow general Natural Language Preprocessing steps (Jurafsky & Martin, 2020; Man et al., 2020; Lamsal, 2020). General cleaning steps include removing punctuation, stop words and nonprintable characters such as emojis from the tweets. In addition to the general steps, techniques such as part of speech (POS) tagging, stemming, and lemmatization, are used widely.

In this research, to increase precision and to facilitate content analysis of the tweets, I used a preprocessing python library named tweet-preprocessor to clean tweets data, removing numbers, URLs, mentions and reserved words (RT, FAV). Since hashtags are part of tweets' content and contain information that shows tweets' topics, I did not remove hashtags. I also kept emoji, emoticon, and punctuation because these will impact sentiment scores.

8.1.3 Sentiment Analysis for Compound Score

I used the Valence Aware Dictionary for sEntiment Reasoner (VADER) to classify the sentiments expressed in Twitter data. VADER is a lexicon and rule-based sentiment analysis tool specifically attuned to social media sentiments(Hutto & Gilbert, 2014; Kumaresh et al., 2019). It can be used to classify tweets as positive, negative, neutral, or compound. VADER informs us about the score of positivity and negativity and tells us how positive or negative the text is. The Compound score is a metric that calculates the sum of all the lexicon ratings which have been normalized between -1(most extreme negative) and +1 (most extreme positive) (Beri, 2020a; Elbagir & Yang, 2019). The compound value is the most commonly used metric for measuring the sentiment in a given tweet (Elbagir & Yang, 2019; Hutto & Gilbert, 2014; Kumaresh et al., 2019; Todi, 2019).

Gilbert developed and compared VADER's effectiveness to eleven typical state-of-the-practice benchmarks, including Affective Norms for English Words (ANEW), Linguistic Inquiry and Word Count (LIWC), the General Inquirer, Senti WordNet, and machine learning-oriented techniques that rely on the Naive Bayes, Maximum Entropy, and Support Vector Machine (SVM) algorithms. The study proves that VADER works better in dealing with social media texts compared with other sentiment analyzers. The study also shows that VADER improved the benefits of traditional sentiment lexicons (Hutto & Gilbert, 2014). VADER was differentiated from LIWC because it was more sensitive to sentiment expressions in social media contexts, and it generalized more favourably to other domains (Kumaresh et al., 2019; Todi, 2019). VADER performs very well with emoticon, slang, emojis, acronyms in sentences. It also takes capitalization into account along with the way the words are written along with their context, such as preceding tri-gram. VADER also considers degree modifiers or intensifiers (modifying words in front of a sentiment term) (Hutto & Gilbert, 2014; Todi, 2019). These words impact the sentiment intensity by either increasing or decreasing the intensity. Another advantage of using VADER is that VADER is typically much faster than machine learning algorithms, as it requires no training, but is built from a generalizable, valence-based, human-cured standard sentiment lexicon (Elbagir & Yang, 2019; Hutto & Gilbert, 2014; Kumaresh et al., 2019; Todi, 2019).

8.1.4 Second Round Tweets Clean

After getting the sentiment scores for each tweet, I removed all punctuation, numbers, emoji, emoticons and converted all uppercase characters to lowercase in preparation for the next step.

8.1.5 Tokenization and Lemmatization

I used the Natural Language Processing (NLP) package Spacy to split the text into sentences and the sentences into words (Tokenization) and remove stop words. After that, I converted words to their root word (Lemmatization) (See Table D2 in Appendix D). Lemmatization is a process of reducing the inflectional forms of words to a common root or a single term (Liu et al., 2012). Compared with stemming, lemmatization considers the context and converts the word to its meaningful base form, whereas stemming just removes or stems the last few characters, often leading to incorrect meanings and spelling (Balakrishnan & Lloyd-Yemoh, 2014; Beri, 2020b; Prabhakaran, 2018b).

8.2 Twitter Data Exploration

8.2.1Temporal Frequency

The COVID-19 outbreak in Canada officially started on March 5, 2020. The WHO declared the COVID-19 outbreak a global pandemic on March 11. Since then, social media platforms have experienced an exponential rise in the content related to the pandemic. From March 13 to March 24, most provinces announced a state of emergency. Provinces announced reopening plans from the end of April (Figure 11).

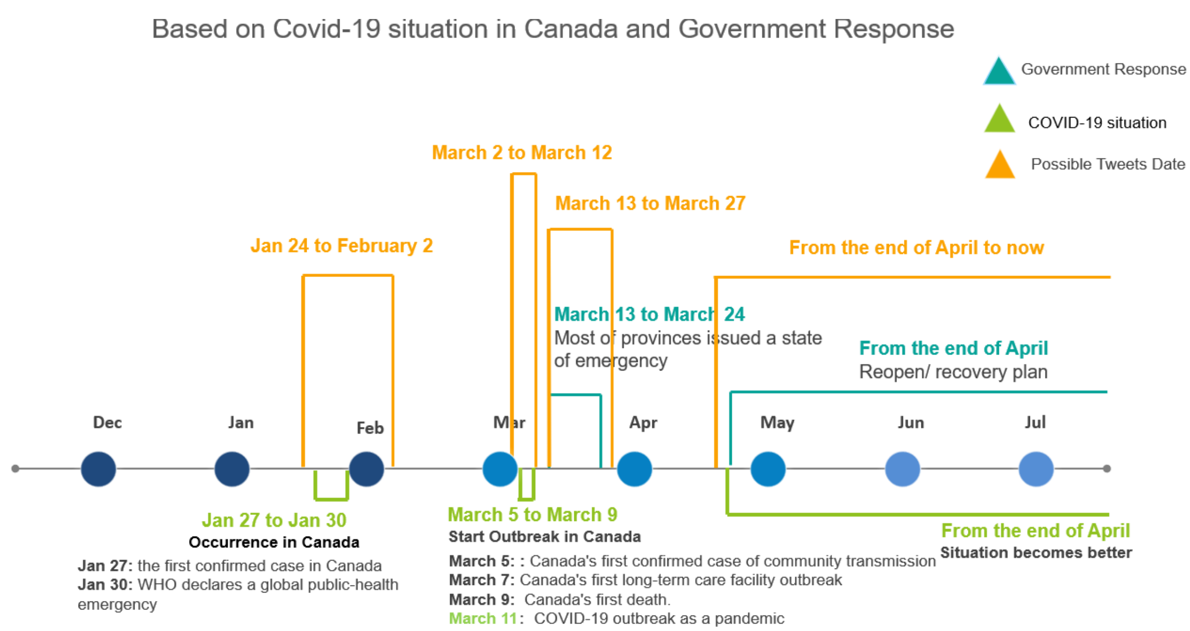


Figure 11 COVID-19 Timeline

Source: created by author

From the temporal frequency results (Figure 12), we can see that in March, April and May, the numbers of tweets are higher than in other periods. It is unclear why the number of tweets started to decline from April. One possible explanation is that most people tend to have more discussions regarding a phenomenon when it is novel, but the discussions may slow down as time progresses.

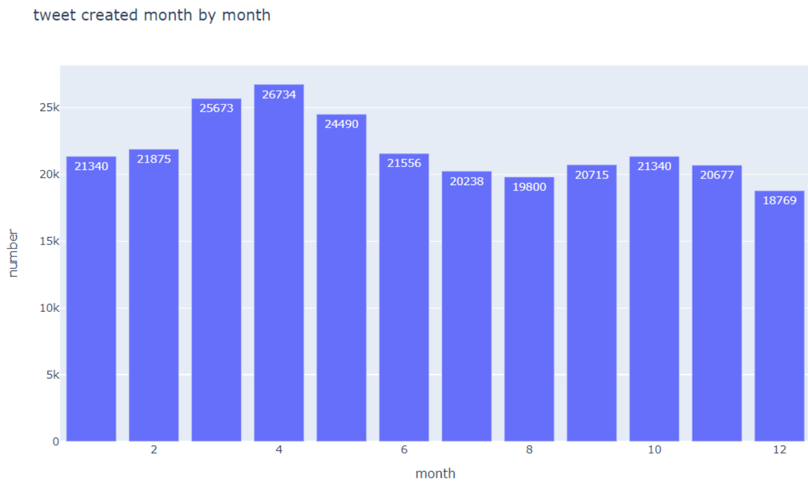


Figure 12 Temporal Frequency of Tweets

Source: author's calculations based on Twitter data

8.2.2 Top Hashtags

The top ten hashtags and hashtag frequency charts are shown in Figure 13. From Figure 13, we can see that COVID-19 was the most used hashtag in 2020. More #covid19 was used after the official name covid-19 was issued on February 11th (Figure 14). Hashtag usage was influenced by pandemic situation and relevant governments responses.

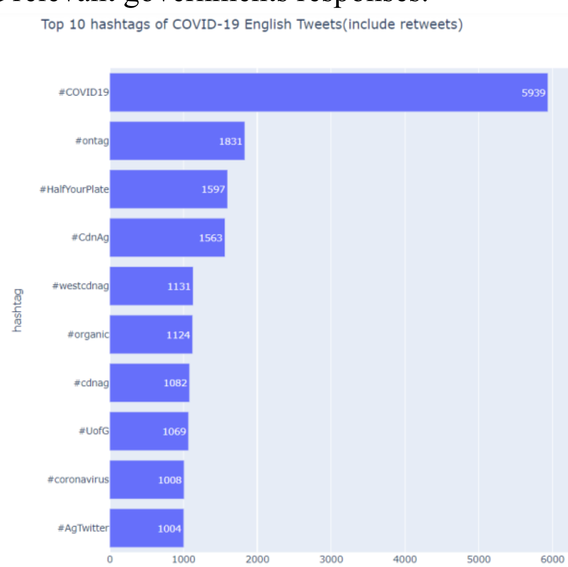


Figure 13 Top Hashtags

Source: author's calculations based on Twitter data

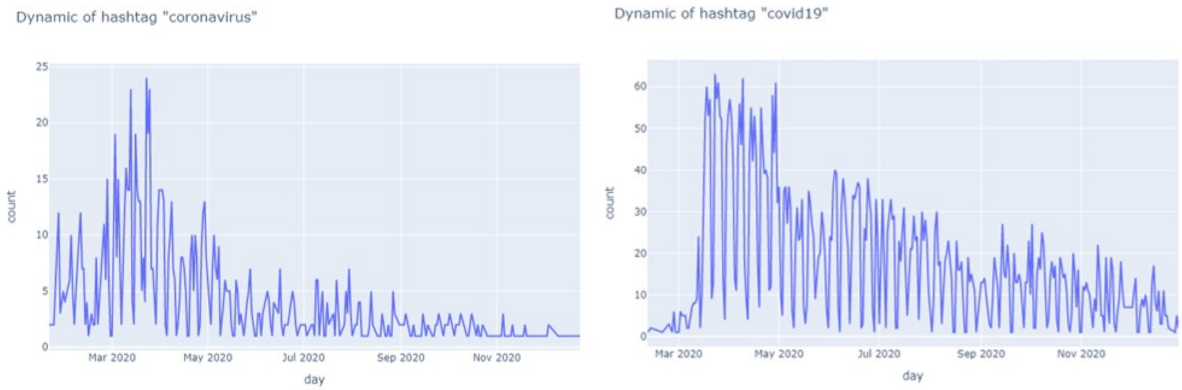


Figure 14 Temporal Frequency of hashtags "coronavirus" and "covid19"

Source: author's calculations based on Twitter data

8.2.3 Sentiment Analysis

The sentiment distribution is shown in Figure 15. Positive sentiment accounts for the largest proportion. After filtering tweets with COVID-19 keywords, the proportions are different. Overall, positive sentiments outweigh negative sentiments. The high proportion of positive sentiments suggests that companies' tweets mainly express positive emotion.

Words "covid"," coronavirus"," pandemic", and" virus" shows in all sentiments tweets (Figure16). After removing these words, we can gain more insight from the most common terms for different emotions. Positive sentiment keywords commonly expressed gratitude for frontline workers and community efforts to support their local community. From negative keywords, we can see that negative sentiment keywords commonly express concerns about the risks and crises caused by pandemic, as well as apologies for delayed response or cancellation. "case", "vaccine"," disease", "fund" and "government "are the most common words in neutral sentiment tweets. These words often appear in the news. This may indicate that companies do not express strong emotions when they are talking about the news.

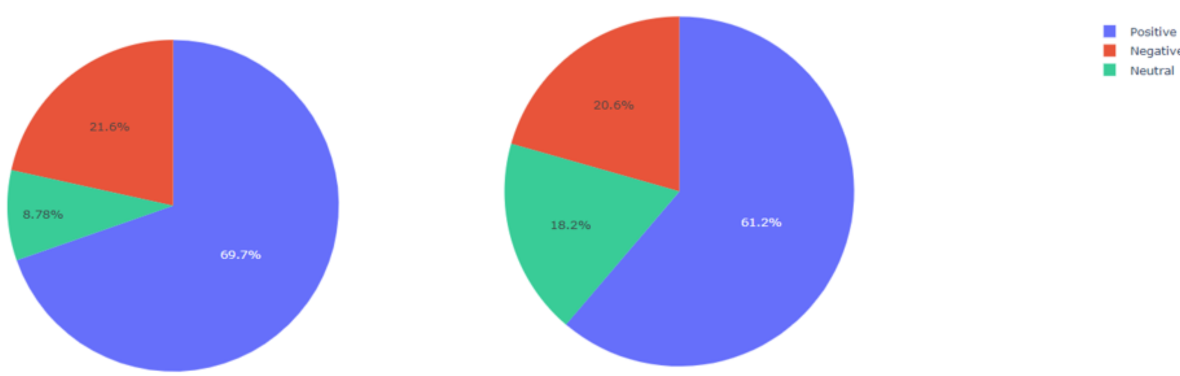


Figure 15 Sentiment Distribution (Left: All Tweets; Right: COVID Tweets)

Source: author's calculations based on Twitter data

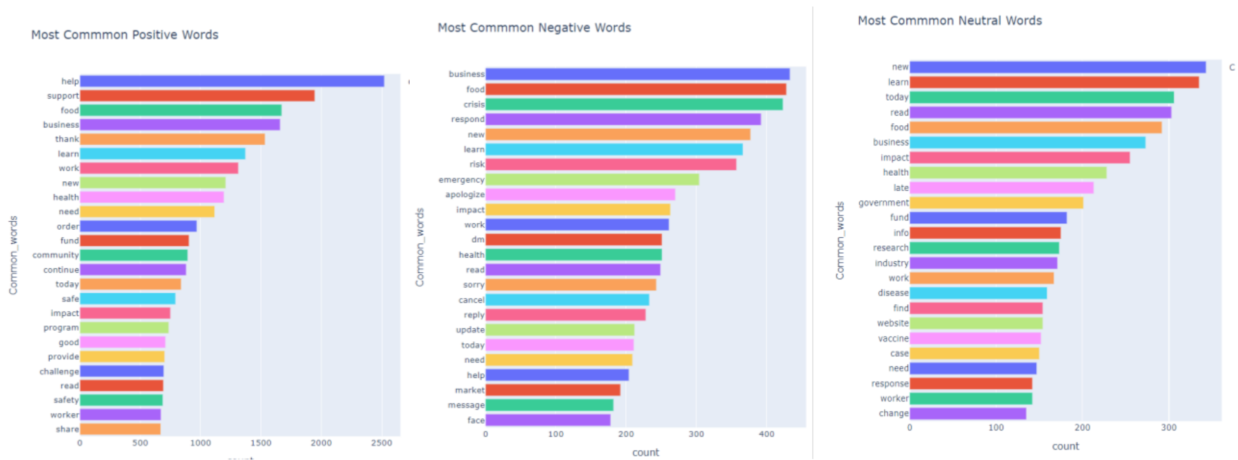


Figure 16 Most Common Words in Different Sentiments Tweets

Source: author's calculations based on Twitter data

8.2.4 Word/Phrases Frequency

Then, I analyzed the collected tweets using word frequencies of single (unigrams) and double words (bigrams) and the results shows as Figure 17. Top words are COVID-19 keywords, such as covid, pandemic, and coronavirus. From Bigram analysis, we can see more COVID-19 information, such as covid pandemic, covid vaccine and public health. There are also some phrases that show companies' attitude and some industrial words, such as fight covid, responses covid, and supply chain. There are some terms about emergency responses, such as Canada emergency and wage subsidy. Some communication words, such as send dm, sorry delay, apologize delay also show up.

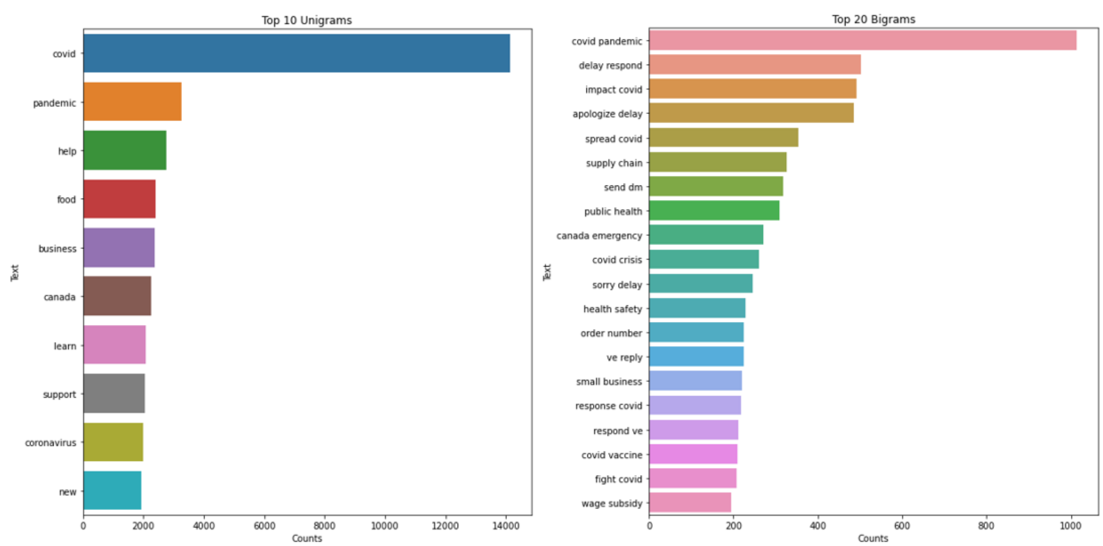


Figure 17 Unigram and Bigram

Source: author's calculations based on Twitter data

8.2.5 Frequency of Usernmaes Tweeting about COVID-19 and Profile

From Figure 18, we can see some companies frequently tweeted on COVID-19. I also checked the top 40 users based on the number of followers. Figure 19 also shows the total number of tweets. After comparing the results of these two figures, I found that some companies that frequently posted COVID-19 information on Twitter have a higher number of followers, such as WalmartCanada, NRC_CNRC, and TD_Canada.

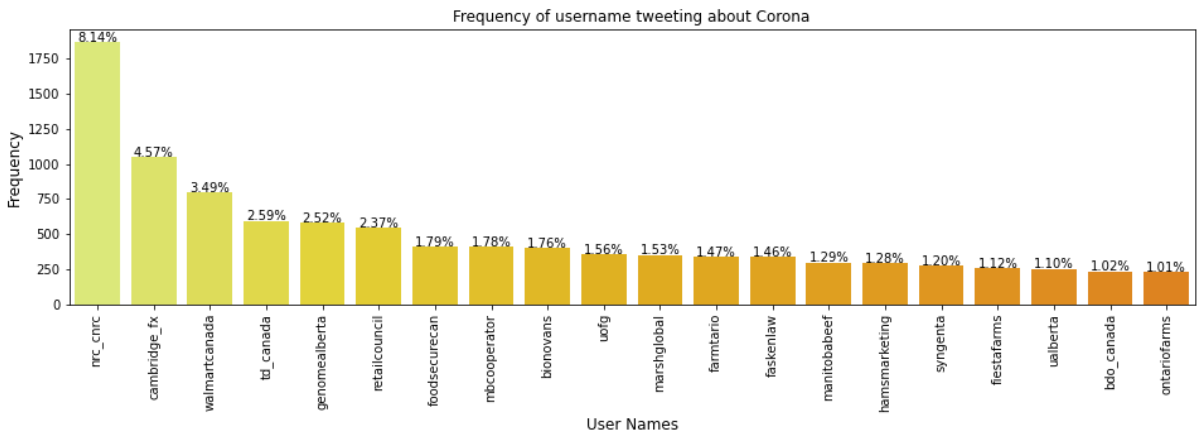


Figure 18 Frequency of Usernames Tweeting about COVID-19

Source: author's calculations based on Twitter data

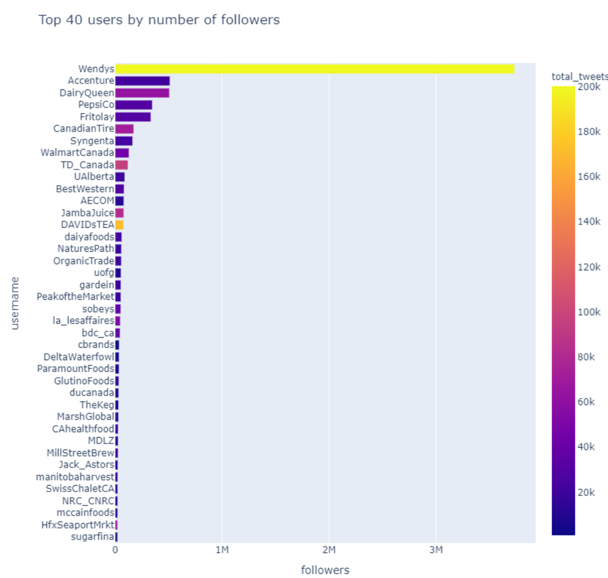


Figure 19 Top 40 Users by Number of Followers

Source: author's calculations based on Twitter data

8.2.6 Topic Modeling

Topic modelling is a type of statistical modelling for discovering the abstract "topics" that occur in a collection of documents. To extract more COVID-19 keywords and get a sense of tweets topics, I conducted topic modelling using NMF (Non-negative matrix factorization) and LDA (Latent Dirichlet Allocation) with Sklearn and Gensim python packages. I also used pyLDAvis package to generate interactive charts to show the keywords and respective topics.

While LDA and NMF have differing mathematical underpinnings, both algorithms can return the documents that belong to a topic in a corpus and the words that belong to a topic. LDA is based on probabilistic graphical modelling, while NMF relies on linear algebra. Both algorithms take as input a bag of words matrix (Kuchkula, n.d.). LDA works better with longer texts such as full articles, essays, and books. Previous studies mentioned that conventional topic modelling schemes, such as Latent Dirichlet Allocation, may perform inadequately when applied to tweets because of the sparsity of short documents (Jónsson & Stolee, n.d.; Ottesen et al., 2017). NMF is simpler than LDA, and it is a better option for analysis on shorter texts if modelling runtime is not a constraint (Habbat et al., 2020; Klos, n.d.; Kuchkula, n.d.; Mahajan, 2020). Mallet's version LDA often gives better quality of topics than Gensim's inbuilt version of the LDA algorithm. In order to find the optimal number of topics for LDA, I built many LDA models with different values of number of topics (k) and pick the one that gives the highest coherence value (The self-defined compute_coherence_values() function trains multiple LDA models and provides the models and their corresponding coherence scores). Picking an even higher k value can sometimes provide more granular sub-topics. Several studies have mentioned this approach (*Gensim - Creating LDA Mallet Model - Tutorialspoint*, n.d.; Kurt, 2020; Prabhakaran, 2018a).

After checking the coherence score, the optimal number of topics is twenty-five (See Figure D1 and Table D 3 in Appendix D). Some topics were identified, such as apologies for late reply, government support, sharing information, COVID-19 test, operation changes, donation, health and safety measures, employee, agri-food industry, supply chain, essential workers, vaccine research, etc. I also checked its interactive chart, and the interactive chart shows the top 30 most salient terms, which can provide more information. After summarizing the results of NMF, Gensim LDA, and Sklearn LDA modelling results, I modified keywords categories and added more words into the COVID-19 keywords list.
Topic model results link:
https://colab.research.google.com/drive/1r8t-TiUSAYkkRMm09o2vdz6kLrYupxKo?usp=sharing

8.3 Keywords List and Tweets Annotation

8.3.1 Process

In the web content analysis step, I categorized companies' responses and generated a COVID-19 keywords dictionary. After finishing Twitter data exploration, I added the top representative terms of each topic produced by topic modelling algorithms and the common words from the word cloud, unigram(n-gram), and bigrams to my keywords list. In this step, I also consulted some external resources to enrich the keywords list, such as Guidance on Essential Services and Functions in Canada During the COVID-19 Pandemic, COVID-19 Guidance for Farmers', Fresh Food & Holiday Markets and List of Essential and Nonessential Businesses under Stay at Home Order, etc. (Canada, 2021; CDC, 2021; *Coronavirus Disease (COVID-19): Guidance Documents - Canada.Ca*, 2020; *COVID-19 Guidance for Farmers' Markets*, 2020; *Personal Protective Equipment (PPE) - Canada.Ca*, n.d.; OSHA/NIOSH, 2020). The keywords' analysis literature also mentioned some COVID-19 relevant hashtags and keywords.

In order to enrich and improve the keywords list, after tweets annotation, I sorted the result based on likes count and manually checked the first 250 rows to see if I missed any relevant keywords. The keywords list was updated several times. Each time I update the keyword, I rerun the annotation code and exported the results to manually check the results to ensure the accuracy of the tweets annotation. Unmarked tweets were also checked to see if more words could be added to the list.

Not every keyword represents a unique response or topic. Thus, I manually cleaned the keywords by removing those that were too generic (e.g., love). This process was carried out in several confirmation processes. In rare cases where I cannot decide, I searched the keywords or hashtags on the original tweets dataset and used the tweets to support the interpretation.

The keywords list and annotation results were then circulated among the team to gain feedback. After several cycles, the keywords list was finalized and used to extract COVID-19 tweets and categorize these tweets into different categories. Tweets annotation was done by python code. In order to get accurate results, I used regular expressions to find exact match, not partial match. For example, if my target is the word "app", the term "application" will not be captured using exact matching.

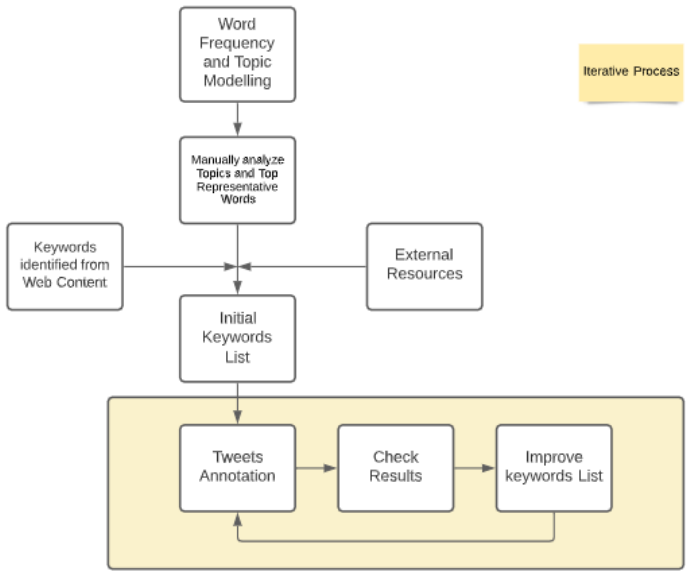


Figure 20 Process of Tweets Annotation

Source: created by author

8.3.2 Final Keywords

Final Keywords have 28 categories, one is COVID synonyms, and the other twenty-seven are responses categories (Table 6).

Table 6 COVID-19 Keywords

Keywords Category	Keywords Example	Explanation
COVID Synonyms	covid, pandemic, virus, coronavirus, epidemic, global health emergency, public health emergency, state emergency, canada emergency, covidcanada, coronaviruscanada, coronalockdown, coronaoutbreak	COVID-19 words, use to extract COVID-19 tweets
Emergency_Response	canada emergency rent subsidy, canada recovery hiring program, canada recovery benefit	Government, organizations and companies' emergency responses
COVID_Workers	cashier, public transit worker, childcare worker, transport driver, truck driver, restaurant worker	People who continue to work during the pandemic
Medical_frontline_worker	frontline worker, essential worker, medical staff	Medical, frontline and essential workers
Employment	job search, return interview, virtualcareerfair, internship opportunity	Employment opportunity
Mental_health	Work life, social isolation, mental health	Mental health relevant keywords
Personal Protective Equipment (PPE)	Mask, face shield, glove	Personal protective equipment keywords
Physical_distance	social distance, limit capacity, physical distancing, contactless	Keywords about physical distance
Hygine_disinfect	wash hand, sanitise hand, handwash	Keywords about hygiene and disinfect measures

Isolate_quarantine	Isolation, quarantine	Keywords of isolation and quarantine
Health and Safety Guidance (hs_guidance)	contact trace, covid alert app, avoid non essential travel	Keywords of health and safety guidance and guidelines
Treatment_test	diagnostic test, coronavirus test, positive coronavirus, vaccine	Keywords of COVID-19 test and treatment
Misinformation	Rumor, misinformation, infodemic	Keywords of misinformation or rumor on COVID-19
Apologize	inconvenience, apologize delay response, long wait time	Apologize to customers for late reply or delay service
Help vulnerable people and community and support local business and community (hvsl)	donate, food bank, homeless shelter, vulnerable citizen, dedicated shopping hour, support local	Keywords of helping vulnerable people and community and supporting local business and community
Adjust_opreation_support	begin produce hand sanitizer, switch hand sanitizer	Keywords show changing operation or production line to produce medical goods
Gratitude and Stay positive (gsp)	thankafarmer, stay positive, strongertogether, incredible work	Keywords about expressing gratitude and encouraging people to stay positive
Recover_reopen	reopen, return regularly schedule, recovery	Keywords of reopen or recovery plan
Information_resource	webinar, town hall, video conference	Keywords about sharing information and resources
Goods_Service	appointment, order online, delivery, carryout, pickup, curbside	Keywords represent companies' goods and services
Social_activity	quarantinerecipe, home gardening, pandemic gardening	Activities recommended by companies
Shutdown_close	shutdown, lockdown, reduce operation hour	Keywords about shutdown, closure and disruption
Digital Transformation (DT)	ecommerce, technology, ai, digitalisation, digitaltransformation	Keywords about digital transformation
Cyber_security	Cyberattack, cyber security,cybercrime, data fraud, phishing scam	Keywords of cyber security
Supply_chain	supplychain, food supply, supply system	Keywords about supply chain
Food_topics	Food security, food justice, food safety	Keywords of food security, food safety, food justice, food sovereignty, food literacy, and food industry future
Panic_buying	Panic buying, toiletpaperpanic, panic shop	Keywords on panic buying
Food_waste	Food waste, food loss, surplus	Keywords about food waste

Source: created by author based on Twitter and web data

8.3.3 COVID Tweets

Keywords from COVID synonymous, PPE, Hygiene Disinfect, Test Treatment, Health Safety Guidance, Isolate Quarantine, Physical Distance, Emergency Response, Medical Frontline Worker, Social Activity, Shutdown, Adjust Operation Support, and Help Support Vulnerable Local categories have been used to extract COVID-19 tweets. There are 24,237 tweets about COVID-19, and most of these tweets are in English.

Table 7 Summary of COVID Tweets Data

Data	Number of Tweets
2020 COVID Tweets	24,237
2020 English COVID Tweets	22,907
2020 French COVID Tweets	1,330

Source: author's calculations based on Twitter data

Table 8 Number of Companies Tweeting in Different Languages (COVID Tweets)

Language	Username Count (COVID Tweets)
English and French	63
Only English	666
Only French	14

Source: author's calculations based on Twitter data

9. Company Responses Identified from Tweets

9.1 Responses

From the final keywords list and tweets annotation results, I identified companies' responses and categorized them into 27 categories.

9.1.1 Personal Protective Equipment (PPE)

Companies post their protective measures and requirements on Twitter. To ensure customers' and employees' safety, companies require their customers to wear masks or face covering when entering the store, and they also provide protective equipment such as plexiglass, face shields, and gloves for their employees. They also share personal protective equipment's suppliers' information.

Table 9 Personal Protective Equipment (PPE)

Responses	Tweets Example
Customer PPE Requirements	With the rising number of COVID-19 cases in B.C, and in light of the recent public health order - we require our guests to: wear a face-covering before coming inside, wear a face-covering when out of your seat (Disposable masks will be provided if you don't have one on you) https://t.co/J9ulrrk9n2
Employee PPE requirements	We are committed to making our stores as safe as possible during COVID-19. We are taking additional measures to protect our employees and you including: adding plexiglass barriers at cash and the option of protective face shields for our employees. https://t.co/4VHceAZ3YP https://t.co/Wl4SDgJMRI
Share PPE supplier’s information	Are you a farmer looking for face masks, gloves, shields and other #PPE to protect your employees from COVID-19? The Ontario government Workplace PPE Supplier Directory has access to over 200 suppliers. #OntAg

Source: created by author based on Twitter data

9.1.2 Physical Distance (physical_distance)

Companies encourage people to follow the physical distance requirement, stay at home, and reduce contact. Some companies announce their work from home directives. Some stores or restaurants reduce their maximum occupancy capacity and demand their customers to follow the physical distance regulations.

Table 10 Physical Distance

Responses	Tweets Example
Work from home	Effective today, OFA has implemented a mandatory work from home strategy in response to COVID-19. OFA's head office in Guelph will be closed until further notice. Business operations will not be interrupted & regular service & support will continue https://t.co/GuRkz4XQT6 #ontag
Stay and home/ Physical distance	We encourage all residents to practice social distancing. Keep a distance of 2 metres from others and limit the number of people you come into close contact with. And if you develop symptoms - stay at home. For more info visit https://t.co/Ge2WXTBY7H https://t.co/NgMBGVnbpe Best way to understand "social distancing" or "physical distancing" = STAY HOME!! #COVID19NS #CoronaVirusCanada
Limit the capacity	Following today's provincial announcement of the new province-wide lockdown, starting December 27th, our stores will remain open and operate at a 25% maximum occupancy capacity. We encourage you to plan ahead, shop online and order Same-Day Pickup where possible, and stay safe.

Source: created by author based on Twitter data

9.1.3 Hygiene Measures (hyginene_disinfect)

Companies keep sanitizing high-touch surfaces, such as doorknobs, handrails, light switches, handles, and shopping carts. They also encourage people to follow hygiene measures to slow down the spread of the virus.

Table 11 Hygiene Disinfect

Responses	Tweets Example
Hygiene measures	We're doing our best to stay on top of sanitizing surfaces, and other high touch areas. And growler fills are temporarily suspended. Worst case, come in, and grab some beers to go. Our fridge is full! High touch items like shopping carts, phones and counters should be regularly cleaned to reduce the spread of COVID-19.
Share information on hygiene measures	When was the last time you washed your hands? REMEMBER: Wash your hands for 20 seconds frequently throughout the day. Use alcohol-based hand sanitizer if soap and water isn’t available. https://t.co/3cz0oC1YCz #COVID19 https://t.co/Nq70WfaKyP

Source: created by author based on Twitter data

9.1.4 Isolation and Quarantine (isolate_quarantine)

Companies remind their audience and require their employees to isolate themselves if they have COVID-19 symptoms, have been tested positive, have been exposed to COVID-19, or return from a trip. Some companies also mention their self-isolation arrangement and policy, including payment, sick leave for their employees. Employees may not get payment during self-isolation, and their isolation may be taken from holidays depending on company policy.

Table 12 Isolation and Quarantine

Responses	Tweets Example
Self-isolate and quarantine regulations and requirements	All employees who are sick, in contact with someone who is sick, or have recently traveled to high-risk destinations have been instructed to self-quarantine for 14 days to protect themselves, other staff members, and our customers
	We are taking important steps to safeguard our customers, colleagues and communities. If you have cold or flu-like symptoms, have been exposed to COVID-19 or have been asked to self-isolate, please avoid our branches. Learn more at https://t.co/CYP70nworg https://t.co/ryMpr1i7qf
Self-isolation arrangement and policy	No self-isolation pay for Richardson employees https://t.co/8pNnru1gKo Documents given to @MBCooperator indicate Richardson International employees forced to self-isolate will need to use holiday or flex time. (1/5) https://t.co/ObBODnOaKr
	FAQ: Do I require a sick note if I am missing school or work or because I am self-isolating? A: Employees and students will not be required to provide sick notes. For employees, this leave will be with pay and not taken from vacation or sick leave https://t.co/VpVJAOPEJ8 https://t.co/xgTpmL2Cik

Source: created by author based on Twitter data

9.1.5 Health and Safety Guidance (HS_guidance)

Companies follow government health and safety guidelines and adjust some measures based on their needs. For example, to reduce the risk of infection, some companies have chosen not to accept cash, instead only allowing transactions to be made through debit or credit. Companies also explain to customers who have questions about their health and safety measures. They also encourage people to follow health and safety guidelines and download the COVID-19 alert App to help stop the spread of the virus.

Table 13 Health and Safety Guidance

Responses	Tweets Example
Share information on health and safety guidance	READ - Recommended #COVID19 protocol for Canadian breweries: https://t.co/nBhF1f9LoE
Encourage the public to follow guidelines	In the spring, we flattened the curve, and we can do it again this fall. Keep following your local public health guidelines and download the COVID Alert app here: https://t.co/Ds1hsQZKQV https://t.co/iFRrnYG8iU
Announce their covid protocol and policy	The Niagara Region has issued new restrictions on businesses such as wineries. Starting Saturday, in addition to our health screening and other COVID-19 protocols, we must ask that all guests booking a Seated Tasting experience with us be from the same household.
	The Ontario Food Terminal Board has established & implemented a covid-19 protocol for the facility. Visit our website https://t.co/Q9s6S3tZr5 for updates!! https://t.co/7iMKlfAGOB
Reply to customers' who have concerns about their covid-protocol	@gamergallant @HalifaxReTales We have very stringent COVID protocols in place but we also totally understand if that's not in your comfort zone!
	@Whitedawgshaw Hi, Health Canada, has confirmed that our protocols follow the recommended and appropriate practices. We strictly enforce; cleaning, disinfection and preventative hygiene. As well, the recommended 14-day self-quarantine period for sick employees or those who travelled recently.
Guidance for their customers	RCC and our retail members are excited to share our #ShopSmart video explaining precautions and guidelines shoppers should follow during the COVID-19 pandemic to keep everyone safe https://t.co/DfXW5f9J1b cc: @RexallDrugstore @McKesson @LongosMarkets https://t.co/lMFT4K7j2S
Refuse to use cash	Effective today, we've made some temporary changes to our Tasting Room: + Reduced hours: 12pm - 6pm + Beer to-go (Cans, Bombers & Crowlers) and take out food orders only + Debit/Credit only. We won't be accepting cash. Stay safe and wash your hands! -Team OYB https://t.co/xqZweWQ31E
Avoid unnecessary travel	Help protect the people we love and keep our schools, businesses and workplaces open, safely. Say 'No' to gatherings with people from outside your immediate household, and avoid unnecessary travel outside your community. Learn more: https://t.co/5CXfmkAhVP #Covid19 #DoYourPart https://t.co/XyQPTIketm
The benefits of contact tracking	Investing in testing, contact tracing, and public health data management will help slow the spread of #COVID19 and prevent future outbreaks. Learn more about the #SafeRestart Agreement: https://t.co/qGpf29Itzl https://t.co/exvNqbKefX
Implement contact track	COVID-19 Update July 26th In response to the latest provincial health order and the recent increase in COVID-19 cases in BC: We are strictly adhering to contact tracing recommendations for the health https://t.co/Qgy34bFPrO
Encourage audience to download app	Together, we can have a positive impact on the health of all. We encourage you to download the free COVID Alert app to help limit the spread of the virus https://t.co/y2Xg5d0Ul5 #AlerteCOVID # COVID19 https://t.co/KAevRTLaMG

Source: created by author based on Twitter data

9.1.6 Treatment and Test (Treatment_test)

Companies inform and notify customers about their employee's confirmed cases. They also share covid test and treatment information with their audiences, including vaccine, medical treatment, screening, and diagnostic test kit.

Table 14 Treatment and Test

Responses	Tweets Example
Inform and notify customers about their employees' positive cases	* COVID-19: Update of April 21, 2020 * We have unfortunately been informed that one of our employees at the SAQ at 7077 avenue Casgrain in Montreal has today been confirmed positive for COVID-19 by Public Health. More info here: https://t.co/klyP8fbUHd https://t.co/lyNlUNgDU3
Share information about covid test and treatment information	Make an appointment for a #COVID19 test today to reduce your wait. Visit https://t.co/SqdbIP7GJp for details. #Covid19MB https://t.co/65679EMapf

Source: created by author based on Twitter data

9.1.7 Misinformation

Companies discuss the risk of misinformation. They hope the public could participate in combating rumours and misinformation. They also respond to their audiences about misinformation or concerns about their products and services.

Table 15 Response to Rumor and Misinformation

Responses	Tweets Example
Misinformation risks	Nearly 50% of Canadians believe a major conspiracy theory when it comes to #COVID19 Misinformation is literally killing us. #cultivatingtrust @FarmFoodCareSK
Prevent misinformation	There is currently no cure for #COVID19. #Physicaldistancing is the best way to limit the spread of COVID-19. Help prevent online #misinformation by consulting trustworthy sources. https://t.co/wiMj3SPDTu 1-833-784-4397@CPHO_Canada https://t.co/OSv4d9oRLm
Recommendations	What's the best defence against a #COVID19 #infodemic? Read through our recommendations. #coronavirus https://t.co/P1YZglajCr
Respond to misinformation	We've been noticing lots of interest in our elderberry products over the past few months and wanted to respond to various concerns and misinformation being shared with respect to elderberry, the SARS-CoV-2 virus/COVID-19, and immune health: https://t.co/o4nmV7NjF0 #BeFloraHealthy https://t.co/MaPKGFiF4G

Source: created by author based on Twitter data

9.1.8 Emergency Response

Companies share information about government, organizations and companies' emergency response programs and relief programs, such as Canada emergency rent subsidy, Canada recovery hiring program, Canada recovery benefit, federal grants, crisis response fund, and sick pay. Some agri-industry relief programs, such as Agri-food Workplace Protection Program, Canadian Beef Cattle Check-Off funds and Organic Farmer Grant, are posted as well. They encourage their audiences to view this information and apply for these programs to relieve their life pressure.

Table 16 Emergency Response

Responses	Tweets Example
Share information about emergency response programs	Emergency Income Relief Fund for the self-employed, Emergency Working Capital Financing for small business, Emergency Relief Worker Assistance Program To apply for all these programs, visit https://t.co/dXHWHJNuyt.
	On @TheCurrentCBC with @mattgallowaycbc, @j4mw stated there are no regs for housing or sick pay for TFWs affected by #COVID19. Housing faces many regs & sick pay is available through EI or CERB. We support the safety & health of TFWs, and honest assessment of our sector. #cdnag
Pandemic pay and increase wage	'The right thing to do': Chapman's Ice Cream makes pandemic pay permanent https://t.co/ZSOcwMj6jW via @YahooFinanceCA
	Three major Canadian grocery chains have brought in wage increases for employees still working the cash registers and keeping the shelves stocked during the ongoing COVID-19 pandemic. @UFCWCanada https://t.co/OvharWIo1l
Subsidy and financial assistance	To support employers in the agricultural and agrifood sectors with their labour needs, we have announced an adjd of up to 50% wage subsidy to enable them to hire young people aged 15 to 30. More info https://t.co/TyGPWQPcd5 #AgCan https://t.co/JAQN6u8Rqy
	Hey, Ontario farmers! Apply now for financial assistance from #CanAgPartnership for projects aimed at improving and growing your business. Info: https://t.co/lYMIOfI2Pg #agriONT #ouvertauxaffaires @OntarioSoilCrop https://t.co/yNxclX5qgY

Source: created by author based on Twitter data

9.1.9 COVID Worker

Companies express their appreciation towards COVID workers and also post support programs and resources for them. Some companies share successful COVID workers' stories to encourage others.

Table 17 COVID Worker

Responses	Tweets Example
Support/Resources sharing /donation/funding	A well-rounded set of resources to help cattle producers deal with ALL of the issues created by the current market disruptions. The list was put together by the @BeefResearch. #westcdnag #cattle https://t.co/gLUGRNnx60
Share program application information	The seed potato growers assistance program can help compensate for the negative effects that COVID-19 has had the industry. Applications are open until January 15, 2021. More details here - https://t.co/OBGNEpJjiU https://t.co/GBYNkJV7l2
Share successful story	Our growers remain committed to producing safe, sustainable vegetables through the COVID-19 pandemic. Read the full article to learn more about how Ontario greenhouse vegetable growers grow food in the face of challenge: https://t.co/eWlA8glB5i #GreenhouseGoodness #CdnAg #OntAg https://t.co/Gp3EG6v8HP
Thanks for workers hard work	Tom's final thoughts: #Thankyou to @CanadianBeef and the #cdnbeef processors who ensured that food was available and made it to consumers' tables throughout the pandemic. Hopefully we have the necessary groundwork to move forward in future crises. #CDNBeefConf

Source: created by author based on Twitter data

9.1.10 Medical and Essential Worker

Companies express their gratitude and provide medical supplies to frontline and medical workers.

Table 18 Medical and Essential Worker

Responses	Tweets Example
Donate protective equipment	We are donating over 500k masks to support frontline healthcare workers caring for Ontarians during the COVID-19 crisis. This vital equipment will be sent to hospitals, long-term care homes & other essential health-care providers. Together we will #PowerON. https://t.co/D8tBS3tEEE https://t.co/Q9w5OfptGK
Express gratitude	Thank you, Shirley, for your work on the frontlines. Your caring and dedication has kept you and our clients safe during the pandemic. #UnsungHeroes #healthcareworkers @coldteamedia https://t.co/bSar0zt7Ot

Source: created by author based on Twitter data

9.1.11 Employment

Companies post job opportunities and share career fairs information with their audiences.

Table 19 Employment

Responses	Tweets Example
Job opportunity or job information	Many Canadians have seen their jobs affected by the COVID-19 outbreak. Now is the time to take advantage of the many employment opportunities available in the agriculture and agri-food sector. https://t.co/C890euWV1V
Job fair	We're glad to be partnering with @OntarioFarms to offer virtual career fairs and other career services during the COVID-19 pandemic. https://t.co/z45kfkXYkZ
Internship opportunity for student	We are partnering with Canadian #CleanTech employers- like @terramera in #Vancouver; to create 900Â internship opportunities for students, as we #BuildBackBetter from #covid19. The program is now open for applications - apply today: https://t.co/dsNXUWUbtd #Environment #Economy https://t.co/O5JUNA1Kru
Hire laid-off workers	Meeting the challenge of COVID-19: Vancouver brewery Parallel 49 is switching to make hand sanitizer, and grocery deliverer Spud is looking to hire 100 laid-off restaurant workers. https://t.co/ZeuzG8rOFm

Source: created by author based on Twitter data

9.1.12 Mental Health

Companies and organizations provide mental health support and help. They attach importance to the mental health of employees and hope that employees can achieve a good work and life balance.

Table 20 Mental Health

Responses	Tweets Example
Mental health help	You don't have to tough it out alone. Struggles with mental health are common in the farming community. Many farmers, producers & family report very high levels of stress, & signs & symptoms of burnout, depression & anxiety. https://t.co/YmYMvMBHJb is Here For You #Farmers Talk https://t.co/g29WUjWxmR
Mental help service	It is important to look after your mental health. Help is available if you just need someone to talk to. Call toll-free and book your first free appointment with a trained counsellor. https://t.co/N4tu7DUaFS #Manitoba #Covid19MB https://t.co/2HKMT2SNdr
Balance work life	As we emerge from this, we'll be in a better position to respond to what workers want - to balance their home and work life, says @RooBristol in a conversation with @Microsoft365's @jared_spataro on how Covid-19 is reshaping the #futureofwork: https://t.co/t3tc95C8Pj

Source: created by author based on Twitter data

9.1.13 Apologize

Companies apologize to their customers for the delay in reply due to the high volume of calls or service requests. They express their apology for causing inconvenience and gratitude for customers' understanding. Some of them also invite customers to leave feedback to improve their further service.

Table 21 Apologize to Customers

Responses	Tweets Example
Apologize for late reply due to high volume call, message, emails	@RMaoula Hello Rami! I regret the delay and confirm that we receive a high volume of calls. In order to better assist you, do not hesitate to write to us in private. Thank you for your patience. -GC
Apologize for delay order	@jimgaut2 Hi Jim, Our stores are processing a much higher demand of orders at this time. We're sorry for any delays in your order and appreciate your patience at this time. Thank you.
Provide their contact information	@karenbellerby Hi Karen, thank you for letting us know about this. Do you have a reservation that you tried to cancel? If so, please contact our Customer Care team at 1-800-528-1238 for further assistance. - Sam https://t.co/AXW7KsaL5V
Collect feedback to improve further service	@ridgers65 Hi Grant, we're sorry to hear this happened. We will share your feedback with this store, directly. Thank you.

Source: created by author based on Twitter data

9.1.14 Social Activity

Companies recommend some activities people can do when staying at home, such as cooking, planting own ingredients in gardens and balconies, exercising. Some companies also share recipes and organize cooking classes regularly.

Table 22 Social Activity

Responses	Tweets Example
Cooking	Beer for breakfast is now totally acceptable. Try this week's #SteamworksQuarantineKitchen Breakfast Beer Bread recipe, courtesy of our lead brewer, Brett! https://t.co/TcFKOrvsdW Join us tonight at 9pm for #ChitChatChop: The Isolation Chronicles! Patricia & Keith from @StreamFinancial and Laura, our long time friend and cooking class fan, will be joining us to get a sneak peek of our NEW Virtual Cooking Classes - coming soon to a monitor near you! https://t.co/9AeMRExhg9
Gardening	First harvest of the balcony-grown radishes https://t.co/npyhIHk4gC for our Easter meals. Gardening is just one of those great activities that all of you can do, easy to start with, will bring the family together and can eliminate stress as well while under lockdown. #AskAkos https://t.co/CzfaTTjJXr
Exercising	Fresh air and exercise are positive ways to cope with feelings of #stress, #disappointment and #anxiety. For more tips: https://t.co/e6b9bmAw5i #COVID19 https://t.co/zTsy7R5TLA

Source: created by author based on Twitter data

9.1.15 Panic Buying

Companies mention the risk of panic buying and hope people will stop this behaviour.

Table 23 Panic Buying

Responses	Tweets Example
Stop panic buying	To all Canadians: Panic shopping is NOT necessary and can even cause more damage than good. As reported by the Government and experts, there are no issues with our current food supplies. #StopPanicBuying #covid19canada #covid19 https://t.co/ehpxdn7oet
Panic buying risks	Panic buying, lockdowns may drive world food inflation. https://t.co/yNI1A0ziNu #COVID19 https://t.co/Sjhd9fjxsM Markets and Grain Prices "Could wheat be the new toilet paper? In these unprecedented times, the international buyers of agricultural products are dealing with two major risks from grain exporting countries infected with COVID: https://t.co/hJbUAM0xOl https://t.co/fW8gEO5iSc

Source: created by author based on Twitter data

9.1.16 Goods and Service

Companies post their goods and services information on Twitter. Some of them provide online ordering, pick up, delivery services.

Table 24 Goods and Service

Responses	Tweets Example
Delivery	We want to help out everyone that may be self-isolating to keep our community safe. Introducing Phillips Ales on Wheels: our new home beer delivery service running Wednesday through Sunday between 4-8pm. For more info: https://t.co/mp2SKZ6Afh https://t.co/hBqkUR2yoy
Pick up and order online service	Hey You! We really appreciate your support at this time. We urge you to call ahead or order online for contactless pick up at the brewery. Reminder: To protect our staff - if you are under quarantine, please do https://t.co/43F157zVcD
Take away	#covid_19 update time! As per Provincial Health Authority Guidelines, we are closing the lounge today, March 17. We will, however, still be open from 2-8 for take away cans and bottles. You can also pick up a gift card for later use! Hopefully, we can #flattenthecurve. Stay safe! https://t.co/S0eXECWu5a
Free shipping	Hold my beer while I order craft beer on the intrawebs from @2CrowsBrewing Use code HRMISOLATION2020 for free shipping in HRM! Thanks 2 Crows! #SelfIsolation

Source: created by author based on Twitter data

9.1.17 Supply Chain

Companies have seen the changes and problems brought about by the epidemic, such as labour shortage and logistics problems. They help governments collect information on supply chain disruptions. They encourage collaboration with each participant in the supply chain. Some companies mention their measures to reduce supply chain disruption and show their confidence in maintaining food supply. They also thank the food supply chain workers for their hard work.

Table 25 Supply Chain

Responses	Tweets Example
Collect Supply chain information	If you're experiencing any shortages due to COVID-19 which could disrupt the #CdnBeef supply chain, please take a second to fill out our survey before 10 a.m. (EST) tomorrow to be included in this week's report to the Federal Government. Click here: https://t.co/eUa6PnbaJL
Express gratitude and support	With much of our province back in lockdown, we'd like to thank the frontline food workers for providing a stable food supply for Ontario. Please continue to support your local butcher shops & restaurants. We're here for you. #cdnFoodHeroes #loveOntFood https://t.co/tQlD3lTzye
Supply chain issues and changes	"As with so many aspects of life, the packaging industry will likely be permanently altered by the pandemic..." Great piece from the folks at @Slate that looks at the supply chain issues caused by the COVID-19 pandemic. https://t.co/ReGLLDrcXL
Logistics issue and labour shortage	Some small pulse buying interest from N Africa and middle east. However logistics, ports, and banks are all issues in these destinations. Closures and labour shortages are being reported in some areas.
Encourage collaboration	Pandemic a threat to global food supply: FAO We need to collaborate with every actor in the supply chain, build public-private partnerships and promote innovation." https://t.co/qJ8LA9kJEw https://t.co/OxW7HyFmYN
	Manufacturers and retailers rely on each other and need to work together towards a stronger Canada. Find out more as @MGraydon_FCPC chats with @RCC's The Voice of Retail on learning from #COVID19 and rebuilding a stronger supply chain than ever before: https://t.co/q6x0NMiiU9 https://t.co/gOh9FPuiS6
Prioritize logistic strategy	The current #COVID19 crisis is a reminder that a well coordinated #logistics strategy should be a priority, says @HarvardBiz #CovidCanada #supplychain #supplychainmanagement https://t.co/XB93DWAL86
Take measure to maintain supply chain	TEMPORARY FOREIGN WORKERS - This is a food security issue. Today we are announcing a new measure to maintain our food supply chain and the health of Canadians. # Polcan #Agcan https://t.co/mlBETXpHlw
Supply chain management	can take comfort in knowing that supply management has ensured that we have a safe and secure food supply during the pandemic @dfc_plc @eggsoeufs @TheInsideCoop @chickenfarmers #CdnDairy #CanadianEggs #PEI #Cdnpoli #SenCA #COVID19
Supply chain innovation	Reducing food shortages through supply chain innovation - op-ed co-authored by Martin Scanlon @umanitoba Rickey Yada @ubcLFS and Rene Van Acker @UofGuelphOAC @agricola373 #COVID19
New measures for import or export	CFIA announces new temporary import requirement: Romaine lettuce from parts of #California must be tested for E. coli. https://t.co/WHuFgCZvmp https://t.co/mQuasO4SNH

Source: created by author based on Twitter data

9.1.18 Shut Down and Close

Companies post their new operating hours or temporary closure, postponing, suspending or cancelling services notice for their customers. Companies are facing labour shortages, and they need to hire workers to maintain their operations.

Table 26 Shutdown Close

Responses	Tweets Example
New operation hours	The @CanBorder is temporarily reducing service hours at the Crystal City, Manitoba port of entry. New temporary hours of service: 9 am to 5 pm, seven days a week. https://t.co/wdwS5LPqXx
temporary closure notice	We have decided to temporarily close our beverage bar, '76 Sips. We look forward to returning to normal operations when the times permit, but will in the meantime be glad to provide your essential necessities at our Lansdowne St and Lindsay locations from Monday to Saturday. https://t.co/25xRyvk8oX
Postpone activity/event	Just a reminder that all AHEM in-person workshops have been postponed until future notice. We will reschedule once the COVID-19 situation stabilizes. Producers are encouraged to maintain/elevate biosecurity on their premises. For more information, visit: https://t.co/CMylVva69Z
Suspend service	With the health & safety of our staff and patrons being our top priority, we have decided to suspend all growler fills (in new and old growlers) until further notice. For more info: https://t.co/vL3mxBIctC https://t.co/HxOqLT6OgI
Destroy products	U.S. dairy farmers dump milk as pandemic upends food markets https://t.co/0tmb2zOuGl
Close border (Import export suspend)	CBSA closes #Thunderbay office temporarily due to #COVID19 Use #PigeonRiver #borders #export #import https://t.co/d3XRlPAPYf
Labour shortage	It takes roughly two untrained people to replace one skilled (temporary foreign worker), so you're looking at a labour shortage of more like the 2,000 to 2,250 range if the borders were shut off today, said Allan Melvin, chair of the @NSFA labour committee.

Source: created by author based on Twitter data

9.1.19 Adjust or Switch Operation

Some companies adjust, switch or change their production lines to produce medical supplies to help fight against virus.

Table 27 Adjust or Switch Operation

Responses	Tweets Example
Produce hand sanitizer	#FridayVedette | Stronger Together: Here's How Green Beaver, Beau's, and Dunrobin Teamed Up To Turn Beer Into Hand Sanitizer During The # COVID19 Pandemic #Braverlacrise https://t.co/5bWaCCLQ09 https: //t.co/hCTxv1v4Kb
Decontaminate masks	Craft brewers across Canada are stepping up to help the fight against #COVID19 in any way they can. Shout out to @steamworksbeer for helping to decontaminate N95 masks and ensuring the safety of our frontline healthcare workers! https://t.co/ZmPntiT9wF
Produce healthy respirator	Thanks to @CAE_Inc for producing healthy respirators for Canadians! 10,000 devices will be distributed across the country to fight # COVID19! #FaitauCanada #PlusFortsEnsemble #Entreprisescdn https://t.co/xzBMSuvrTY
Produce face shields	Owners of 3D printers are helping a #SwiftCurrent resident to produce protective face shields for frontline health care workers. #COVID19 #COVID19Sask https://t.co/vpgW81Cnyj

Source: created by author based on Twitter data

9.1.20 Gratitude and Stay Positive (Gsp)

Companies express their gratitude towards workers and provide additional payment for them. They also express appreciation to their customers, thanks for their patience and understanding. They hope people can stay positive and optimistic. They also highlight the importance of collaboration, including international collaboration, industry collaboration and collaboration among business and governments.

Table 28 Gratitude and Stay Positive

Responses	Tweets Example
Express their gratitude towards essential and medical workers, for their hard work and dedication	"Thank you to all doctors, nurses, first responders and essential business workers! You are Canadaâ€™s heroes. #ThankYouThursday #COVID19 https://t.co/X1qkxNaYfA"
Express gratitude towards their employees and provided hero pay	"Members of the @CanadianForces work hard every day and are doing an extraordinary job to help keep us safe. This #ThankYouThursday, we thank our members in uniform for their dedication to helping Canadians during this challenging time. #COVID19 https://t.co/1X5dBarm1W". "We are so thankful to our retail and distribution teammates who are working the frontlines to deliver essential services to Canadians during #COVID19. We are proud to support them with our new "Hero Pay Program". Read the latest from our CEO, Michael Medline. https://t.co/1iMloHuBi4" Thank you to all in the agri-food industry for your continued service during this pandemic. We truly appreciate it! #WeFeedTogether
Express gratitude to their customers	The hours of all Choices locations have changed temporarily. We appreciate your patience and understanding during these unprecedented times. Please check out our website for the store hours update all the details on our response to COVID-19: https://t.co/FAbs0TRjyr https://t.co/94xPHZRlFR
Encourage people to remain positive and optimistic	"COVID-19 has presented big challenges, but Vancouver's craft beer community is working hard to stay positive https://t.co/VKGNHh5IQY"," We all need to play our part to be #StrongerTogether and beat coronavirus."
Highlight the importance of communication and collaboration	"The importance of collaboration & working together in times of crisis, particularly in the context of supporting agricultural development, can't be understated #COVID19 " "COVID has highlighted the importance of effective collaboration. Our team meets frequently in a safe manner, to tackle daily challenges head-on as a collective. Covid has changed many things around the office, but not our commitment to collaboration! #covid19business #leadership https://t.co/MRb7RjrpoC". "Working together, we can help solve some of the world's biggest problems, from sustainable #food production to treatments for #COVID." - @karnmanhas, our Founder & CEO on the power of #Collaboration"
Share information about their collaboration with other companies or organization	"#cdnbeef industry leadership response to #covid19, from policy to government engagement to #communications." " A collaboration between the National Research Council of Canada (NRC) and the Chinese firm CanSino Biologics will allow the manufacture and clinical development in Canada of a candidate vaccine against COVID-19. https://t.co/2GEUTixRzI https://t.co/JaesCp579y"

Source: created by author based on Twitter data

9.1.21 Help vulnerable people and community and support local business and community (hvsl)

The coronavirus pandemic has impacted many small, essential and local businesses that have struggled to stay afloat, even with government support and COVID-19 financial aid. Companies encourage people to shop locally and support local business. Vulnerable communities and people need more help to get through this challenging period. Companies donate food and raise money to support people in need. Stores also reserve shopping hours for seniors.

Table 29 Help vulnerable people and community and support local business and community

Responses	Tweets Example
Support local business	ICYM: We are standing with you through this Covid-19 crisis. Please support local businesses if you can and stay safe! https://t.co/Q5iUpTGpay https://t.co/tiNkpsdekb
Support local community	Looking for a way to help your local community during #Covid_19? Donate some of the following to @ourplacesociety ðŸ™Œ
Provide food and donate money	Help support @aplaceforfood's Good Food Access Fund by sharing their message or donating. They're helping vulnerable communities who are hit hardest during #COVID19 by providing them with nutritious meals and emergency relief. https://t.co/qFYRpnbpym #charitytuesday Georgetown residents raised the most money through the Beer Store's summer fundraiser across Ontario. Funds raised were donated to the Georgetown Hospital Foundation. https://t.co/KU6YebbClb
Food bank	Due to COVID, millions of families are in need of extra help. @naturespath has pledged to donate #OneMillionBowls of food to food banks, pantries, and grassroots groups in the US + Canada! Thank you for the delicious granola and EarthÂ + Element bowl! #EatWellDoGood https://t.co/9eNrVDzQLy
Dedicated shopping hour	The dedicated shopping hour will begin on Tuesday, March 17th and will be in place until further notice. We are asking that all customers respect this temporary measure to provide additional time and space for those most vulnerable. #COVID19NL

Source: created by author based on Twitter data

9.1.22 Share Information and Resources

Companies organize several activities to share information and resources with their audiences. They organize webinars and town hall meetings to discuss the topics that people are most concerned about. They also post frequently asked questions for audience reference. They invite people to join discussions and share their stories and feedback. Some relevant data and resources are also shared or mentioned in their tweets.

Table 30 Share Information and Resources

Responses	Tweets Example
Organize webinars, webcast and discussion	Here is the summary of a meeting with Jean-Philippe Gervais, vice-president and chief economist of @FACagriculture during a webinar on the threats and opportunities of COVID-19. @SollioCoop https://t.co/u8umHWpyV9
Organize town hall meetings/ video conference	Producers in district 2, 4, 6, 8, 10, 12, 14: there is still time to register for your town hall meetings on Oct. 29 and Nov. 5: https://t.co/FVY6bih49c Drought, pandemic focus of beef producer meetings - via @thecarillon https://t.co/YB0OZKOe19
Frequently asked questions	Are you facing a potential disruption to your business as a result of COVID-19? A force majeure clause may apply. This blog outlines frequently asked questions about force majeure clauses to help you navigate your contracts. Continue reading: https://t.co/GWwo4iwWEc #forcemajeure
Share resource	Here's an extensive resource on how to help out during the pandemic. https://t.co/RE7AlcKvpP

Source: created by author based on Twitter data

9.1.23 Digital Transformation (DT)

Companies have established digital platforms to continue to provide services to customers. They encourage others to transform to e-business and share some digital transformation programs that people can apply, such as Digital Main Street. They also discuss the technologies that can be applied in the agriculture industry, such as artificial intelligence. Some technologies can be utilized to switch production lines or operation quickly to produce medical goods, such as 3D printing.

Table 31 Digital Transformation

Responses	Tweets Example
Agri-tech	Clean-tech #startup fusing AI & #Science to create revolutionary #technology to transform how we grow food & solve world challenges @Terramera has increased Series B funding to $48.5m with Canadas #Arctech @agfundernews #agritech #AgTech #farming
Disseminate digital transformation program information	Ontario and Canada are partnering to help small businesses get online and expand e-commerce following COVID-19 through Digital Main Street, including grants of $2,500 per small business. https://t.co/tvlEDFPlXw https://t.co/xnG4ZMYZuC
Build digital platform to continue serve clients/customers	Dear Clients, As the virus continues to spread in communities across Canada, we have made the important decision to continue to provide our services to our clients through a digital office space (email or phone) moving forward. Please visit https://t.co/RpctgZLDSg.
Choose e-business	Businesses play a critical role in the economic recovery from #COVID19. If you feel ready to grow your global presence, #ecommerce could be the right choice. Get the support you need to succeed: https://t.co/1wO34ZpNIs https://t.co/4zSXTE7Vfw
Technology benefits	An empty warehouse in St. John's will soon be a 3D printing farm, where thousands of #covid19nfld face shields will be made for healthcare workers Meet @poly_unity, the startup behind it all https://t.co/3vZUzr6pQV https://t.co/jpAbAAEMi

Source: created by author based on Twitter data

9.1.24 Cyber Security

Companies remind the public to pay attention to scams and fraud. Some tips and guidance on cybersecurity also be shared with their audiences.

Table 32 Cyber Security

Responses	Tweets Example
Watch out for scams	Watch out for #COVID19 #phishing scams. Be wary of some of the information being circulated via social media or that you may be receiving in your inbox. Protect yourself by staying informed: https://t.co/sE8dxE91eS https://t.co/djG7iF0flv
Cyber security measures	Due to the fear and anxiety surrounding COVID-19, and the strategies cybercriminals use to exploit individuals, it is crucial to take appropriate cybersecurity measures to protect your organization. These measures are outlined in our blog: https://t.co/WuUvTGKIhg #privacy https://t.co/DUHeFVEoIs
Tips and guidance for cyber security	As coronavirus re-emerges around the globe, we feel it is important to remind about a few simple yet essential tips for everyone who is working from home. Stay safe! Link: https://t.co/BkKOzc4ezD #CyberSecurity #secondwave #technology https://t.co/hrpXRB6PeI

Source: created by author based on Twitter data

9.1.25 Food topics (food security, food safety, food justice, food sovereignty, food literacy, food industry future)

During this COVID-19 crisis, there is increasing discussion on food industry-relevant topics such as food security, food safety, food justice, food sovereignty, food literacy, and the food industry future.

Table 33 Food industry Prospect

Responses	Tweets Example
Discussion on food security, food safety and food sovereignty	What is the impact of the # COVID19 pandemic on the number of Canadians experiencing #Food Insecurity? New data from our online panel survey, conducted in May 2020, is now available: https://t.co/jSrZjceVxb. # santecan https://t.co/tH4Gkco0rs "Food security, food sovereignty top of mind for First Nations." In B.C, wildfires, floods and now the pandemic make harvesting traditional foods a real challenge for the Tlesqox of Tsilhqotin. https://t.co/HWXtdFn86u
Discussion on food justice	To Shannon Ebron, "food justice really does start at school." For the new Director of Child Nutrition, transitioning districts amidst a pandemic & racial equity movement is a challenge she's gearing up for. Check out her #HeroHighlight story: https://t.co/9oApBwrMKs https://t.co/Ej51x18Rb0
Discussion on food literacy	On April 21 @ 1 pm EDT, join @SustainOntario in a talk on providing food literacy education for children and youth during school closures. Panelists include @lspoonful @FoodShareTO and others â€“ https://t.co/euxeD5BtL5
Discussion on the prospect of food industry	GlobalData Food analyst Andy Coyne sees increased plant-based meat sales post COVID-19. He notes an uptick in China as things return to normal, and points to COVID-19's link to animal protein & health + wellness considerations as factors. #FutureOfFood https://t.co/mUtIVJGF67

Source: created by author based on Twitter data

9.1.26 Food Waste

Companies discuss the food waste problem to raise people's awareness. They encourage people to limit grocery shopping trips and plan their shopping in advance to reduce food waste. Some companies are also involved in food waste programs, such as Food Rescue Program, to reduce food waste.

Table 34 Food Waste

Responses	Tweets Example
Contribute to reduce food waste	Today is the first-ever International Day of Awareness of Food Loss and Waste. The #GoC is contributing to the reduction of food loss during #COVID19 through the $50M Surplus Food Rescue Program: https://t.co/S7rqQLg6Uk #FLWDay https://t.co/2TG7AkAsIB CPMA is working with Second Harvest to apply for funding from the $50 million Surplus Food Rescue Program. Answer poll by June 23 if you have produce surpluses. @CPMA_ACDFL @SecondHarvestCA @AAFC _Canada https://t.co/Lw7edzbJIJ https://t.co/vwVXX8T5y1
Raise people's awareness of food waste problem	Limit trips to the grocery store by planning your meals and snacks. You will also save money and reduce food waste. Learn how to #mealprep like a pro: https://t.co/Lt7MRvGPnA #COVID19 https://t.co/yoHZ4fZU8B

Source: created by author based on Twitter data

9.1.27 Recover and Reopen

Companies announce their reopening information, including reopening plan, new schedules, and operating hours. Companies also share information about post-pandemic measures and reflection on the crisis, such as maintaining business continuity, implementing risk management and improving supply chain resilience.

Table 35 Recover and Reopen

Responses	Tweets Example
Announce Reopen Plan	Vancouver's Chinese restaurants and #dimsum spots are reopening! Your dining experience is going to look very different from pre-COVID times, but that doesn't mean your har gow and siu mai will taste any different.Here's my latest for @MONTECRISTO_Mag https://t.co/u09FNJwIVd https://t.co/tBaq5Qz38V
Thoughts, reflection and discussion on future direction (businesses and industry continuity, resilience, risk management and innovation)	COVID-19: Incorporate Lessons Learned Into Your Business Continuity Plan https://t.co/kW1eeEwtVC https://t.co/Rxv1DhQvBy
	On #CattleCountry, ABP Chair @NuHavenKelly gives an industry update on Covid-19. "Our conversations with government have shown strong support for agriculture and emphasize the importance of our resilient industry in the coming year." Listen here: https://t.co/xzw1LXcopP https://t.co/zmvEDj14JW
	The agriculture sector and global economy are changing. Share your views on business risk management, resiliency, innovation, technology, and market opportunities. Log in to Engage MB today. https://t.co/AbFGwNPb80 #MBAg https://t.co/UGfTsHfm21

Source: created by author based on Twitter data

9.2 Compare Responses Identified from Websites and Tweets

After comparing the Twitter analysis results with web analysis results, I found that more detailed and various responses can be identified from tweets (Figure 21). Social media possesses characteristics of participation, openness, conversation, community, and connectedness (Chisenga & Chande, 2012). As an instant messaging platform, Twitter is more dynamic and can publish content more frequently than websites. In addition, the content of Twitter is more emotional and informal.

Twitter is more like an information center than a website. Some information and notifications, such as confirmed cases, security updates and operational changes, are more likely to be posted on Twitter. Companies also share and update information about emergency response programs and benefits for their audiences on Twitter. Webinars and virtual meetings information are also shared more often on Twitter.

Twitter becomes a place for companies to express their concern, support, and apology. Companies tweet a lot about staying positive and express their support and gratitude to workers. Mental health and work-life balance content appear more often on Twitter. Companies also organize or recommend some activities, such as cooking and gardening, for their audience to do during quarantine. Some companies are actively involved in discussing the development and direction of the industry, such as digital transformation, cyber security and the prospects of the food industry. More social responsibility content has been released on Twitter, such as switching the production line into the production of medical supplies and supporting vulnerable groups. Companies also utilize Twitter to express apologies to their customer for delayed replies or orders.

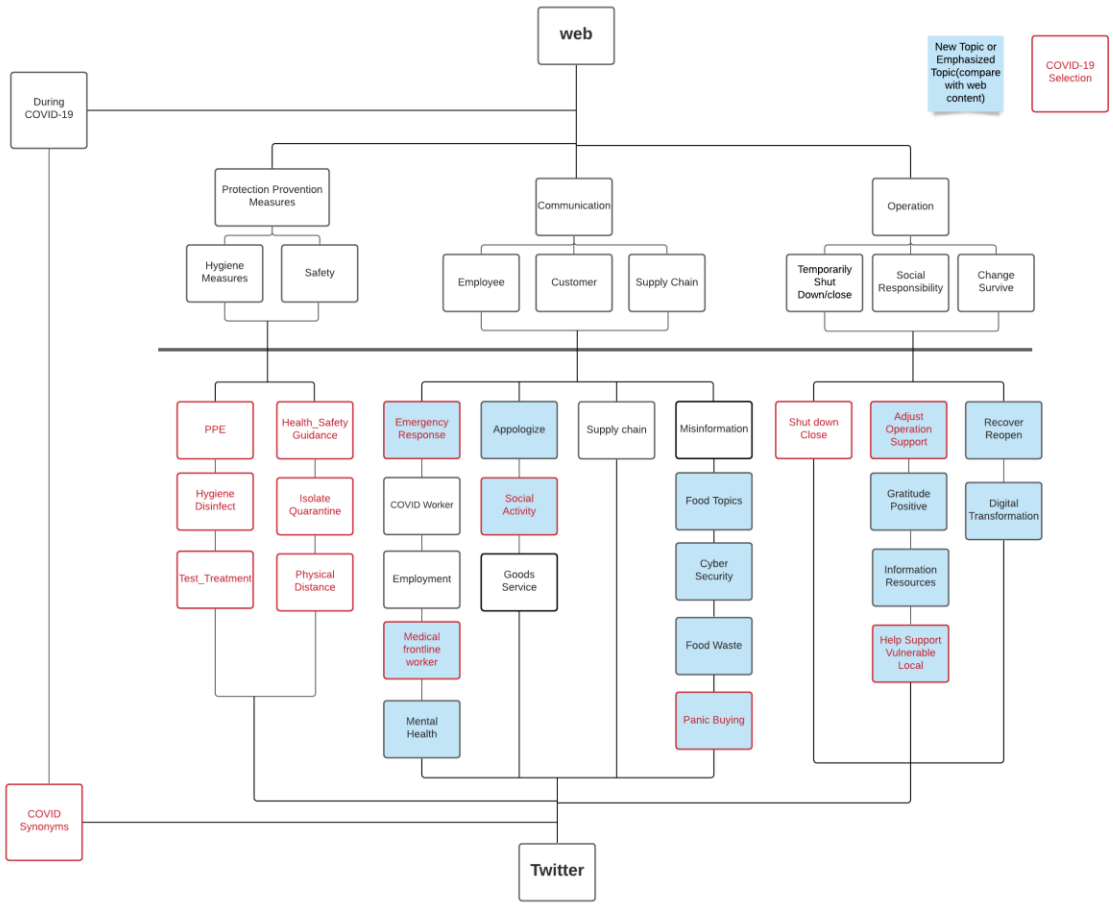


Figure 21Compare Responses Identified from Web and Tweets

Source: created by author based on web and Twitter data

10. Twitter Regression Analysis

10.1 Hypotheses for Research RQ2

The part is for RQ2: What are the relationships between the communication of corporate responses and their reception among social media users?

H2: There will be more interactions (likes) when the responses express more concern for employees, consumers and communities.

After identifying companies' responses in previous section, detailed hypotheses for each response category can be derived from H2.

10.1.1 Responses Express Concern for Workers

The emergency plans, subsidies and benefits of the government and the company can alleviate the financial pressure of employees to a certain extent. Since the outbreak of COVID-19, front-line workers, essential workers and other workers have continued to work hard to provide goods and services to others. They deserve admiration and respect. COVID-19 may change people's attitudes towards work. In the next era of work, people may demand more flexibility and balance in their professional lives. Besides, people are more likely to work for supportive employers who actively encourage their workers to maintain a healthy work-life balance and emphasize well-being (Brown, 2020). According to Edelman (2020) company report, companies who protect the well-being and financial security of their employees can win or maintain the confidence of their consumers. Thus, I hypothesized that: H2-1: There will be more likes when the responses express more concern for workers.

10.1.2 Health and Safety Measures

To protect people 's health and safety, the government announced various measures and regulations. These regulations restrict people's movement and social interaction. Public health requirements, such as physical distance, conflict with the natural human desire for social interaction (Cohen, 2004; Kayes et al., 2020). Thus, at first, there is widespread dissatisfaction with social distancing as a policy, and some people some people are unwilling to comply with this requirement (Benham et al., 2021; Kayes et al., 2020; Mat Dawi et al., 2021). There also exist several obstacles to wearing face masks, including that mask may be difficult for some individuals to wear due to medical reasons and might make communication difficult. Other identified barriers included cost, difficulty with enforcement, and lack of education on wearing a mask properly (Benham et al., 2021; Bhatt et al., 2020; Kayes et al., 2020; Mat Dawi et al., 2021). Regarding the contact tracing app, the main concerns around using a contact tracing app are privacy and security (Ashkan Soltani et al., 2020; Benham et al., 2021; Patrick Howell O'Neill et al., 2020). Some people are concerned about government tracking and surveillance, which was due in part to misconceptions about how the apps work (Ashkan Soltani et al., 2020). Also, barriers to vaccine uptake include a lack of confidence that a vaccine will work and the potential side effects (Benham et al., 2021; Presseau, Arnason, et al., 2021; Presseau, Desveaux, et al., 2021). As the government keeps supplying information related to COVID-19 and educating people on protective behaviour, people's attitudes towards health and safety measures start to change (Mat Dawi et al., 2021). Some scholars conducted research within focus groups or using case study to collect public opinion on health and safety measures (Benham et al., 2021; Kayes et al., 2020). According to their research results, there was a good general understanding among the survey respondents about COVID-19, personal preventive measures and population-level strategies. Participants responded that masks, sanitizers, handwashing, and proper lockdown would help prevent the disease. According to what has been mentioned above, hypothesis 2-2 was put forward: H2-2: Tweets that mentioned health and safety measures are more likely to get likes.

10.1.3 Responses Express Concern for Consumers

Customers may not be able to receive companies' timely replies, or their order might be delayed due to the supply chains disruptions, higher demand, and uncertain timelines with third-party logistics companies (M. Dixon et al., 2020). Due to work-from-home order and public spaces closure, people are turning to find activities that they can do while self-quarantined. Activities, such as cooking and baking, provide comfort and entertainment to people's life (Chittal, 2020 B.C.E.). Canadian consumers flocked to online shopping during the lockdown(*CBC News*, 2020). People spending more time online shopping and updated goods and service information will help them place the order. Thus, hypothesis 2-3 was proposed: H2-3: There will be more likes when the responses express more concern for consumers, except for apology tweets.

10.1.4 Responses Express Concern for Community

More and more consumers realize the importance of corporate social responsibility activities. The rise of social media platforms provides companies with the opportunity to effectively communicate these initiatives to consumers (Chae, 2021). Companies that carry out actions to contribute to society at crisis time are more likely to be remembered by their customers (Batista et al., 2020; Edelman, 2020). Thus, the following hypothesis was put forth: H2-4: There will be more likes when the responses express more concern for community.

10.1.5 Discussing Hot Social Topics

Shocking or emotionally charged content gets people's attention (Abdelsalam et al., 2020; Aslam et al., 2018; Mao, 2020; Naeem, 2021). Tweets about panic buying, food industry topics (food justice, safety), food waste, misinformation, and cyber security are more likely to attract audience attention. Companies proposed some measure or share their attitudes towards these hot topics, which may gain more likes. Thus, hypothesis 2-5 was proposed: H2-5: There will be more likes when the companies discussing hot social topics.

10.1.6 Digital Transformation Responses

As mentioned in the literature review part, the COVID-19 crisis is likely to accelerate the shift to digital significantly. In response to government restriction measures, businesses began to adopt new ways to continue their operations remotely (Almeida et al., 2020; R. Y. Kim, 2020; Lee & Trimi, 2021; Raab & Griffin-Cryan, 2011). Thanks to the internet and technology, businesses turned to various online platforms to remain engaged with their colleagues, clients, and customers while working from home offices. Digital transformation allows more workplace flexibility, and introduces automation and faster processes (Fitzpatrick et al., 2020; McKinsey, 2020). Thus, I hypothesized that: H2-6: Digital transformation tweets are more likely to get likes.

Other hypotheses for companies' responses are proposed based on the literature review section, common sense and the average number of likes for each topic. Detailed hypotheses are listed below (Table 36).

Table 36 Detailed Hypotheses for RQ2

Hypothesis	Sub-hypothesis
H2-1: There will be more likes when the responses express more concern for workers.	H2-1a: Emergency response tweets are more likely to get likes
	H2-1b: COVID-19 Workers tweets are more likely to get likes
	H2-1c: Medical_frontline workers tweets are more likely to get likes
	H2-1d: Employment tweets are more likely to get likes
	H2-1e: Mental Health tweets are more likely to get likes
H2-2: Tweets that mentioned health and safety measures are more likely to get likes.	H2-2a: PPE tweets are more likely to get likes
	H2-2b: Physical distance tweets are more likely to get likes
	H2-2c: Hygiene disinfect tweets are more likely to get likes
	H2-2d: Isolate and quarantine tweets are more likely to get likes
	H2-2e: Health and safety guidance tweets are more likely to get likes
	H2-2f: Treatment test tweets are more likely to get likes
H2-3: There will be more likes when the responses express more concern for consumers, except for apology tweets	H2-3a: Apology tweets are less likely to get likes
	H2-3b: Social activity tweets are more likely to get likes
	H2-3c: Goods and service tweets are more likely to get likes
H2-4: There will be more likes when the responses express more concern for community.	H2-4a: Tweets mentioning switching or adjusting operation to produce medical supplies are more likely to get likes
	H2-4b: Tweets expressing gratitude and encourage people to stay positive are more likely to get likes
	H2-4c: Information and resources sharing tweets are more likely to get likes
	H2-4d: Tweets about helping vulnerable people and community and supporting local community and business are more likely to get likes
H2-5: There will be more likes when the companies discussing hot social topics	H3-5a: Cyber security tweets are more likely to gain likes
	H2-5b: Food waste tweets are more likely to get likes
	H2-5c: Misinformation tweets are more likely to get likes
	H2-5d: Tweets discussing food topics are more likely to attract likes
	H2-5e: Panic buying tweets are more likely to get likes
H2-6: Digital transformation tweets are more likely to get likes	
H2-7: There will be more likes when the responses express concern for supply chain	
H2-8: Shutdown and close responses are less likely to get likes	
H2-9: Recover and Reopen tweets are more likely to obtain likes	

Source: created by author

10.2 Variables

10.2.1 Independent Variables and Dependent Variable

User engagement involves interaction with posts on social media and the level of participation in the post. It is about measuring the interactions that the audience makes with content. User engagement can be a metric of success on social media (Kerry, 2014; Kirtiş & Karahan, 2011; Schroeder, 2013). Social media engagement of users extends beyond passive behaviours, such as viewing or reading posts to more active forms, such as liking posts, commenting or replying, and sharing posts (Barger & Labrecque, 2013; Bonsón & Ratkai, 2013; Cho et al., 2014; Delahaye Paine, 2011). Social media participation includes three main activities: expressing enjoyment, directly responding to messages or dialogue, and voluntarily re-transmitting a message to their own social networks (Cho et al., 2014; Delahaye Paine, 2011). Bonsón and Ratkai (2013) suggested that social media engagement is comprised of three metrics: (1)popularity which refers to the number of likes a post receives; (2)commitment that is captured with the number of comments made by users on posts; (3)virality that accounts for the numbers of shares on posts. Similarly, Barger and Labrecque (2013) defined four types of engagement metrics "expressing agreement," "rating," "voicing opinion," and "sharing".

Retweets, likes, comments are the most common metrics that are used to measure online engagement, and they have different meanings for users. Understanding this difference is important for understanding people's interest in Twitter(Devereux et al., 2020; G Gorrell et al., 2014; Grover & Kar, 2020, 2020; Hollebeek et al., 2014, 2014a; D. Lee et al., 2018; Leman, 2011; Munaro et al., 2021; Oh et al., 2018; Sekimoto et al., 2020; So et al., 2015). Retweet (RT) is a function that allows users to share news, tweets, and other information that was already posted by others. Users retweet content which they found useful. According to So et al.'(2015)s research, retweeting does not only express agreement or support emotion since retweeting also allows comments to be added before the tweets(G Gorrell et al., 2014; Oh et al., 2018; Sekimoto et al., 2020). Users retweet more if the tweets generate amusement, invoke contentment, surprise, and anger. In contrast, likes was formerly called favorites, and it is a function that allows users to share their positive feelings about certain content. Previously, liking was a user's personal favourite feature and did not affect the spread of tweets, but recently likes has become a more meaningful action since liked tweets have been displayed to other users (Sekimoto et al., 2020). Likes becomes an effective indicator for highlighting popular content among individual users and guides businesses to make social media strategy towards finding the most efficient way to appeal to their followers(Devereux et al., 2020; G Gorrell et al., 2014; Grover & Kar, 2020; D. Lee et al., 2018; Oh et al., 2018; Sekimoto et al., 2020).

Likes and retweets are not at the same level of engagement. Paine (2011)mentioned that engagement can be divided into different phases, starting with clicking and liking, continuing with commenting, following, retweeting, and hash-tagging, and finally evolving into advocacy. Furthermore, Gorrell and Bontcheva (2016) explained that likes on Twitter indicate bookmarking of the tweet, whereas a retweet is the next level of engagement where the people endorse the content and propagate it in their personal social network. Compared with liking and sharing, commenting is a heightened form of engagement, above simply interfacing with social media (Oh et al., 2018). Commenting engages users in interpersonal conversations with those who have posted the tweets. Commenting represents a higher level of engagement because it requires a higher level of attention and involvement with the post than "liking" or "sharing" (Genevieve Gorrell & Bontcheva, 2016; Hollebeek et al., 2014, 2014b; D. Lee et al., 2018).

The dependent variable of this study is likes_counts. Likes can show people's positive feelings directly, and it can be treated as phase one interaction of user engagement. My primary focus is on the Twitter likes count prediction for different companies' responses in this study. All response variables are independent variables and encoded as dummy variables, 1 for Yes,0 for No(Table 10).

10.2.2 Control Variables

According to Muñoz-Expósito et al. (2017)'s research on metrics for engagement in Twitter, the format of the content (text, URLs, multimedia content), the type of content (commercial, informative, news), language style (formal, informal, technical), and time of publishing can influence user engagement.

(1) User-related features

User-related features can influence the engagement. Due to that 'follower' relationship, a network of Twitter users emerges in which users are nodes that are connected with each other via edges represented by follow relationship. Suh et al. (2010) pointed out that the number of both followers and following affects the number of times a tweet is retweeted on Twitter. Amjad and Zahra (2017) found that a tweet from a widely connected user has a higher chance to be liked by a wide range of followers. Experience also influences engagement. Arguello et al. (2006)found that posters were less likely to get a reply if they were newcomers.

(2) Content features

Tweets include different components, not only texts but also photos, videos, URLs, hashtags and mentions. These features are designed to facilitate message diffusion to increase audience exposure and serve as stimuli to influence viewers' perceiving and consequent engagement (Han et al., 2019; Hwong et al., 2017; Pancer & Poole, 2016). However, previous works found that these features' effects on user engagement are uncertain. Some of them may even decrease likes and retweets. One general explanation is that these features increase disfluency and make the message less visually clear (perceptual disfluency) and require the translation of symbols and text strings into meaning (orthographic disfluency) (Pancer & Poole, 2016).

Hashtags (word prefixed by '#' symbol) are used to index expressions into a searchable link, facilitating a search for a specified topic of interest. The use of hashtags linked to keywords in tweets can help organize content and improve content discovery. Users can simply engage in the conversation happening around hashtags (Han et al., 2019; Huang et al., 2010; Soboleva et al., 2017; Pancer & Poole, 2016). Tweets with hashtags have a significant probability of being found by users who do not follow the tweet's sender, but who are sufficiently interested in the hashtag's topic. Companies use hashtags to supplement brand image, build community, launch campaigns and engage directly with consumers (Kristie & Byrum, 2014; Han et al., 2019). Therefore, the inclusion of a hashtag in a tweet is reasonable to be perceived to influence consumers' engagement (Han et al., 2019; Soboleva et al., 2015; Suh et al., 2010). However, the effect of including one or more hashtags in a tweet may be non-linear. One study found that tweets containing one to three hashtags are more likely to be retweeted than tweets without hashtags, but as the number of hashtags in a tweet grew, the average number of retweets decreased (Jenders et al., 2013; Soboleva et al., 2017).

Mentions("@") include other users in the content of the tweets and is a form of interactivity (Soboleva et al., 2017). Users who are mentioned in posts receive a notification when they log onto the site. The use of mentions allows these users to join the conversation and be recognized by viewers quickly. Mentions ("@") is sometimes used to mention authors of work referenced, brands' stakeholders(celebrities or influencers), somebody who may be interested in the work or somebody who may help disseminate tweet (Bao et al., 2018; Pancer & Poole, 2016). The function of mention celebrities or influencers is similar to celebrity endorsement, enhancing the followers' positive attitude (Tang et al., 2015). Previous studies have examined the effect of mentions on user engagement and found varying results: either absent effect of mentions on retweeting (Petrovic et al., 2011), a marginal negative effect (Suh et al., 2010) or a significant negative effect (Tan et al., 2014). Some scholars also found that the effect of a mention might depend on whether it is at the start of a tweet (an 'initial mention tweet') or elsewhere within the tweet (Soboleva et al., 2017). A mention at the start of a tweet can capture the attention of a mentioned person, which accomplishes what has been called 'addressivity' (Honeycutt & Herring, 2009). A mention elsewhere in a tweet, while lacking the addressivity of an initial mention tweet, is also likely to draw the attention of the mentioned person, thus potentially resulting in increasing users' engagement (Soboleva et al., 2017).

Users can embed links to external websites in their posts (Hwong et al., 2017).These links provide users with access to extra information interactivity (Burton & Soboleva, 2011) and hyperlinked tweets are considered more informative (Alonso et al., 2010; Sedhai et al., 2014). Several findings suggest that tweets with URL links, on average, are retweeted more often (Naveed et al., 2011; Son et al., 2013). However, according to Soboleva et al. (2017) 's study, the effect of URL links varies across industries, in some cases decreasing the retweet rate.

In addition to the tweet's textual components, the probability of a tweet being retweeted, liked, shared is likely to depend on visual tweet features as well. Since 2013, Twitter allows users to embed videos (and photos). Thus, users do not need to click the URL link to leave Twitter to view the video (or photo). Instead, the tweet itself expands to show the content (Cooper, 2013). Images can project meanings that cannot be expressed via words (De Vries et al., 2012). Conflicting evidence exists on the effect of images in tweets, with one study finding that tweets with photo links do not impact retweetability (Malhotra et al., 2012) and others reporting that tweets with links to photos are retweeted more than tweets without links (Bruni et al., 2011; De Vries et al., 2012; Soboleva et al., 2017). However, users can include more than one photo in a tweet, and it is not clear whether containing more than one photo will increase the frequency of retweeting or decrease retweeting due to increased visual complexity in the message (Soboleva et al., 2017). Videos on Twitter have been shown to enhance the richness of content and help marketers with different tasks from promotion to problem resolution (Leek et al., 2016). Twitter users may thus have higher engagement with tweets containing video content (Soboleva et al., 2017).

(3) Sentiment

Social media post contents show different sentiments, and the sentiment of tweets posted by creators may influence users' engagement. The sentiment of tweets posted by the company can influence consumer's engagement as a strong argument with emotion offers a convincing manner (Kristie & Byrum, 2014). The sentiment of a tweet has been found to have a direct impact on citizens' engagement in government tweets (Zavattaro et al., 2015). However, according to Han et al. (2019)'s research, the sentiment of the tweets) do not directly influence users' engagement of the tweet, which is different from public common sense.

According to previous research on tweets features, the content features of tweets, sentiment of tweets and user related features will influence user engagement. Differences in tweets features and Twitter user profiles are controlled by setting hashtags count, URLs count, photos count, compound, language, mentions count, followers, followings, and total social media accounts as control variables (Table 37).

Table 37 Regression Variables

Variable	Description	Values	Type
likes_counts	number of likes for each tweet	Numerical	Dependent Variable
Compound	Sentiment score of tweet	Numerical	Tweets Level Control Variable
Urls_count	The number of URLs in each tweet	Numerical	Tweets Level Control Variable
Mentions_count	The number of mentioned users in each tweet	Numerical	Tweets Level Control Variable
Photos_count	The number of photos in each tweet	Numerical	Tweets Level Control Variable
Hashtags_count	The number of hashtags in each tweet	Numerical	Tweets Level Control Variable
Language (Lang)	Tweets language	Categorical (French, English) Dummy Variables (1 for en, 0 for fr)	Tweets Level Control Variable
Responses Types	27 types (categorical variables to show if tweet contains certain keywords)	Categorical (Yes, No) Dummy Variables (1 for Yes, 0 for No)	Independent Variables
followers	The number of users who follows the author of a tweet	Numerical	Company level Control Variable
following	The number of users that the author is following	Numerical	Company level Control Variable
Total social media accounts	The number of social media accounts	Numerical	Company level Control Variable

Source: created by author

Table 38 Descriptive Statistics for Numeric Variables

Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
replies_count	24,237	0.31	10.34	0	0	0	1,536
retweets_count	24,237	128.82	3,261.16	0	0	5	205,887
likes_count	24,237	3.67	94.66	0	0	2	14,255
hashtags_count	24,237	1.18	1.71	0	0	2	18
photos_count	24,237	0.30	0.52	0	0	1	4
mentions_count	24,237	0.66	0.89	0	0	1	13
urls_count	24,237	0.51	0.52	0	0	1	5
total_social_accounts	24,237	3.56	1.10	1	3	4	6
following	24,237	1,589.89	2,175.28	0	452	1,704	51,832
followers	24,237	28,254.06	85,045.26	0	1,759	23,639	3,734,212
compound	24,237	0.25	0.44	-0.97	0.00	0.64	0.99

Source: author's calculations based on Twitter data

10.3 Factor Analysis (Validity of Measurements)

In addition to the specific topics discussed in the previous section, I am also interested in the broader category of the COVID-related responses. To help the data interpretation, I planed to use factor analysis to reduce the number of variables. I calculated the number of times each topic was mentioned for each company to get numeric value first. Then, I tried to perform factor analysis to search for influential underlying factors or latent variables from the 27 items.

When running a factor analysis, we need to specify how many components (or latent variables) to retain or extract. Many methods exist to address this issue statistically, but there is no consensus on which method to use or which is the best. These methods can sometimes give very different results (Makowski, 2018; *Structural Models (EFA, CFA, SEM...) • Parameters*, n.d.). To get the factor number that has the highest consensus, I chose the Method Agreement procedure implemented in the psycho package (Makowski, 2018), which proposes to rely on the consensus of methods rather than on one method in particular. This method runs all the routines and returns the number of factors with the highest consensus.

The number of factors that most methods suggest is one and twenty-six (Figure 23 and Table 39). One means all the variables should be loaded into 1 factor, and twenty-six indicates that most of the factors only have one variable (Figure 24). According to this result, I decided not to do factor analysis. I then fitted the Generalized Linear Models (GLM) to the 24k data set to capture the degree to which the probability of likes can be predicted from all the variables in Table 37.

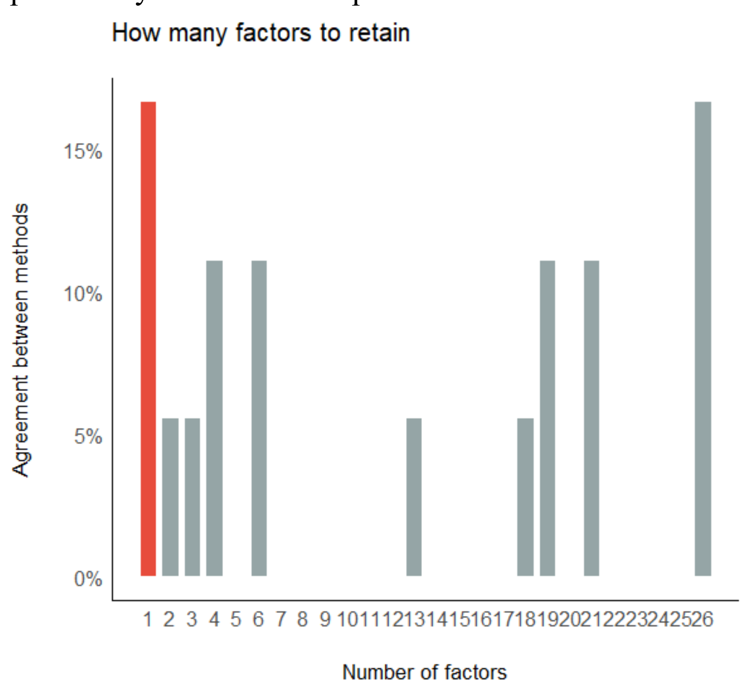


Figure 22 The Number of Factors

Source: created by author based on factor analysis result

Table 39 The Method Agreement Procedure

Number of factors	Method	Family
1	Acceleration factor	Scree
1	TLI	Fit
1	RMSERA	Fit
2	R2	Scree_SE
3	CNG	CNG
4	beta	Multiple_regression
4	Optimal coordinates	scree
6	Parallel analysis	scree
6	Kaiser criterion	scree
13	SE Scree	Scree_SE
18	Bentler	Bentler
19	CRMS	Fit
19	BIC	Fit
21	t	Multiple_reression
21	p	Multiple_reression
26	Bartlett	Barlett
26	Anderson	Barlett
26	Lawley	Barlett

Source: created by author based on factor analysis result

Variable	MR4	MR1	MR18	MR2	MR21	MR5	MR22	MR9	MR10	MR8	MR3	MR12	MR6	MR14	MR13	MR11	MR19	MR7	MR20	MR23	MR17	MR25	MR16	MR24	MR15	MR26	Complexity	Uniqueness
Treatment_test	0.98																										1.00	5.15e-03
PPE		0.97																									1.00	5.00e-03
isolate_quarantine			0.98																								1.00	0.03
Supply_chain				0.96																							1.01	0.07
shutdown_close				0.32																							8.85	5.00e-03
gsp					0.96																						1.01	0.07
employment						0.92																					1.01	0.18
Emergency_Response							0.93																				1.00	0.13
apologize								0.93																			1.01	0.12
Goods_Service									0.91																		1.01	0.21
cyber_security										0.79																	1.02	0.44
food_topics											0.82																1.01	0.27
social_activity												0.74															1.07	0.36
panic_buying													0.75														1.04	0.36
adjust_opreation_support														0.63													1.17	0.48
hvsl															0.65												1.27	0.14
food_waste																0.60											1.10	0.60
COVID_Workers																	0.46										2.68	0.22
DT																		0.39									4.40	5.00e-03
recover_reopen																		0.26									7.40	5.00e-03
medical_frontline_worker																			0.38								3.88	0.02
information_resource																				0.26							7.70	5.00e-03
hygiene_disinfect																				0.25							6.19	0.07
mental_health																					0.30						6.67	0.04
physical_distance																					0.22						12.07	5.00e-03
rumor																						0.37					4.54	0.03
HS_guidance																							0.29				6.11	5.00e-03

The 26 latent factors (oblimin rotation) accounted for 85.60% of the total variance of the original data (MR4 = 6.12%, MR1 = 6.90%, MR18 = 6.37%, MR2 = 4.98%, MR21 = 5.33%, MR5 = 4.63%, MR22 = 6.18%, MR9 = 3.91%, MR10 = 4.45%, MR8 = 3.59%, MR3 = 3.39%, MR12 = 3.20%, MR6 = 2.53%, MR14 = 2.96%, MR13 = 2.24%, MR11 = 2.05%, MR19 = 1.63%, MR7 = 1.74%, MR20 = 1.80%, MR23 = 1.96%, MR17 = 1.29%, MR25 = 2.20%, MR16 = 1.74%, MR24 = 1.65%, MR15 = 0.98%, MR26 = 1.79%).

Figure 23 Factor Analysis Result

Source: created by author based on factor analysis result

10.4 Cross Tabulation

I generated the frequency chart for the number of topics. From the below chart (Figure 25), we can see after tweets annotation, most labelled tweets contain one to two topics. I created the cross-tabulation for responses categories variables (only consider Yes). As can be seen from Table 40 and Table 41, although there are cross classifications, most of the percentages are below 10%. Some high percentages indicate the topics are usually mentioned together. For example, the percentage of digital transformation and reopen_recover is 38.65% since digital capabilities help businesses to recover from the COVID-19 crisis. The percentage for supply chain and panic buying is 43.48%. Companies alleviate customers' panic buying behavior by telling customers that the supply chain can provide enough goods.

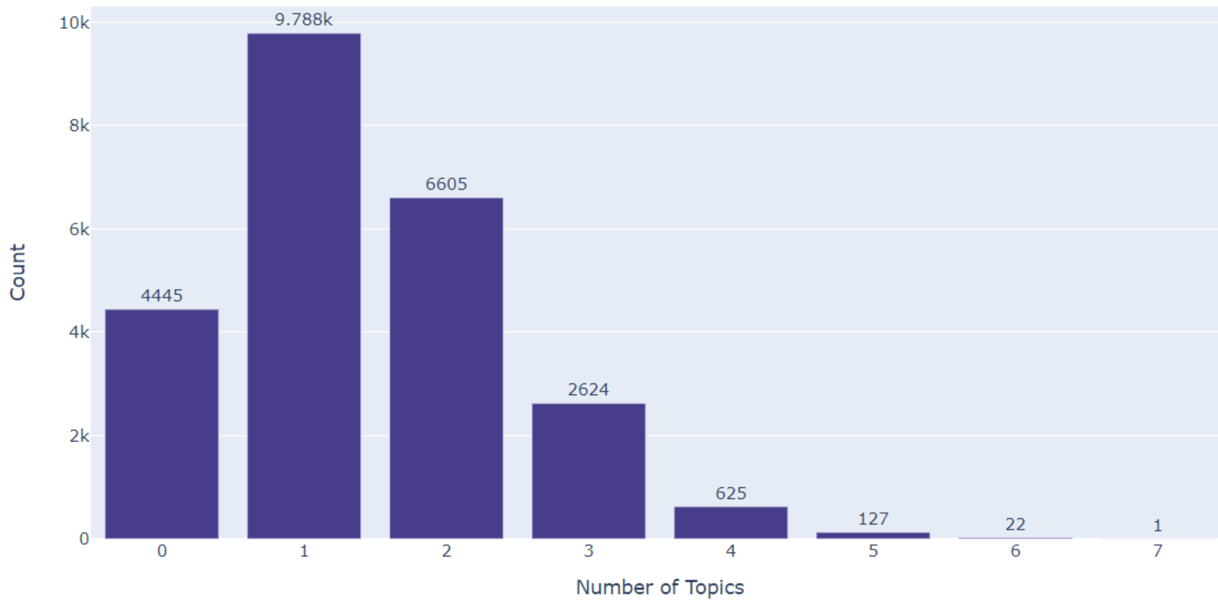


Figure 24 Frequency Chart for The Number of Topics

Source: author's calculations

Table 40 Cross Tabulation

	Emergency_Resp	COVID_W	medical_f	employme	mental_h	PPE	physical_	hygiene_c	isolate_q	HS_guida	Treatment	hvsl
Emergency_Response	100.00	12.30	8.51	18.76	6.12	5.54	4.70	2.91	1.69	0.81	2.43	30.72
COVID_Workers	7.65	100.00	4.38	5.83	3.74	9.04	7.10	2.40	6.65	3.25	1.62	12.31
medical_frontline_work	3.75	3.11	100.00	2.91	7.14	16.79	5.90	7.53	4.27	3.25	16.42	9.16
employment	3.90	1.95	1.37	100.00	5.44	0.92	2.13	0.51	0.40	0.54	0.46	0.81
mental_health	0.68	0.67	1.80	2.91	100.00	0.00	2.24	0.51	5.26	1.36	0.12	1.83
PPE	1.14	2.98	7.82	0.91	0.00	100.00	6.34	15.41	3.67	2.98	2.08	6.21
physical_distance	3.26	7.92	9.28	7.10	13.95	21.40	100.00	24.32	16.67	20.60	4.62	4.98
hygiene_disinfect	0.64	0.85	3.78	0.55	1.02	16.61	7.76	100.00	5.56	5.42	5.32	1.42
isolate_quarantine	0.64	4.08	3.69	0.73	18.03	6.83	9.18	9.59	100.00	7.32	4.05	1.63
HS_guidance	0.11	0.73	1.03	0.36	1.70	2.03	4.15	3.42	2.68	100.00	1.62	0.92
Treatment_test	0.80	0.85	12.20	0.73	0.34	3.32	2.18	7.88	3.47	3.79	100.00	0.61
hvsl	11.44	7.37	7.73	1.46	6.12	11.25	2.68	2.40	1.59	2.44	0.69	100.00
adjust_opreation_supp	0.00	0.18	0.69	0.36	0.00	1.11	0.27	0.86	0.10	0.27	0.00	0.10
gsp	13.72	12.24	25.00	5.28	6.46	16.42	11.14	8.22	6.35	10.03	6.94	25.74
recover_reopen	17.51	19.43	11.86	22.40	14.97	14.02	17.20	16.10	8.63	14.09	10.75	11.29
information_resource	7.58	13.22	7.56	16.21	27.89	3.32	10.38	8.22	7.14	7.32	3.58	6.41
rumor	0.04	0.06	0.26	0.18	0.34	0.55	0.22	0.51	0.20	0.27	0.23	0.20
apologize	2.61	2.31	0.69	0.73	1.02	1.48	1.91	0.86	0.69	1.08	0.92	1.63
Goods_Service	2.77	2.68	3.44	1.09	2.04	3.87	5.13	1.20	4.07	2.98	2.20	8.75
social_activity	0.61	0.43	0.52	0.91	1.02	1.11	2.46	0.34	2.88	0.81	0.00	1.32
shutdown_close	2.88	11.81	3.18	7.47	3.40	5.17	10.16	4.45	2.68	2.71	1.16	14.24
DT	5.19	3.17	6.36	4.01	4.42	6.83	3.50	4.28	1.29	3.79	5.90	2.03
cyber_security	0.68	0.12	1.46	0.73	0.68	0.00	1.47	0.86	0.40	0.81	0.69	0.41
Supply_chain	4.28	16.63	8.68	5.83	1.36	13.28	8.25	6.51	3.77	4.07	4.97	8.04
food_topics	1.67	4.93	1.55	1.09	0.34	0.18	5.24	1.20	0.60	0.81	0.12	4.07
panic_buying	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.27	0.00	0.31
food_waste	0.19	0.43	0.09	0.00	0.00	0.18	0.16	0.00	0.00	0.00	0.00	0.92

	adjust_op	gsp	recover_r	informati	rumor	apologize	Goods_Se	social_ac	shutdown	DT	cyber_sec	Supply_ch	food_topi	panic_bu	food_waste
Emergency_Response	0.00	13.32	10.78	6.61	1.49	3.68	8.90	5.67	2.62	12.85	7.23	4.61	11.20	0.00	14.29
COVID_Workers	7.14	7.40	7.44	7.17	1.49	2.03	5.37	2.48	6.69	4.88	0.80	11.13	20.61	0.00	20.00
medical_frontline_work	19.05	10.71	3.22	2.91	4.48	0.43	4.88	2.13	1.28	6.94	6.83	4.12	4.58	0.00	2.86
employment	4.76	1.07	2.87	2.94	1.49	0.21	0.73	1.77	1.41	2.06	1.61	1.30	1.53	0.00	0.00
mental_health	0.00	0.70	1.03	2.71	1.49	0.16	0.73	1.06	0.35	1.22	0.80	0.16	0.25	0.00	0.00
PPE	14.29	3.27	1.77	0.59	4.48	0.43	2.56	2.13	0.97	3.47	0.00	2.94	0.25	0.00	2.86
physical_distance	11.90	7.51	7.35	6.28	5.97	1.87	11.46	15.96	6.42	6.00	10.84	6.16	24.43	0.00	8.57
hygiene_disinfect	11.90	1.77	2.19	1.59	4.48	0.27	0.85	0.71	0.90	2.35	2.01	1.55	1.78	4.35	0.00
isolate_quarantine	2.38	2.35	2.03	2.38	2.99	0.37	5.00	10.28	0.93	1.22	1.61	1.55	1.53	0.00	0.00
HS_guidance	2.38	1.36	1.21	0.89	1.49	0.21	1.34	1.06	0.35	1.31	1.20	0.61	0.76	4.35	0.00
Treatment_test	0.00	2.21	2.17	1.02	2.99	0.43	2.32	0.00	0.35	4.78	2.41	1.75	0.25	0.00	0.00
hvsl	2.38	9.31	2.59	2.08	2.99	0.85	10.49	4.61	4.83	1.88	1.61	3.22	10.18	13.04	25.71
adjust_opreation_supp	100.00	0.29	0.07	0.07	0.00	0.11	0.37	0.00	0.07	0.09	0.00	0.69	0.00	0.00	0.00
gsp	19.05	100.00	9.61	8.16	2.99	18.23	22.20	5.67	14.32	9.66	2.81	13.70	11.20	13.04	20.00
recover_reopen	7.14	15.16	100.00	27.26	16.42	11.46	17.07	9.57	13.01	38.65	12.85	17.33	13.49	8.70	14.29
information_resource	4.76	9.09	19.24	100.00	13.43	17.59	5.61	3.55	7.32	14.82	14.86	8.64	16.28	4.35	0.00
rumor	0.00	0.07	0.26	0.30	100.00	0.11	0.00	0.35	0.00	0.56	2.01	0.00	0.00	0.00	0.00
apologize	4.76	12.58	5.02	10.91	2.99	100.00	8.41	1.77	9.32	1.97	2.81	6.48	0.76	0.00	0.00
Goods_Service	7.14	6.70	3.27	1.52	0.00	3.68	100.00	5.67	6.52	2.91	0.40	4.77	5.09	8.70	14.29
social_activity	0.00	0.59	0.63	0.33	1.49	0.27	1.95	100.00	1.86	0.28	0.00	1.51	2.80	0.00	2.86
shutdown_close	4.76	15.27	8.79	7.01	0.00	14.39	23.05	19.15	100.00	7.22	10.04	22.71	5.60	13.04	8.57
DT	2.38	3.79	9.61	5.22	8.96	1.12	3.78	1.06	2.66	100.00	17.27	5.30	4.58	0.00	5.71
cyber_security	0.00	0.26	0.75	1.22	7.46	0.37	0.12	0.00	0.86	4.03	100.00	0.37	0.00	0.00	0.00
Supply_chain	40.48	12.36	9.91	7.01	0.00	8.48	14.27	13.12	19.22	12.20	3.61	100.00	25.45	43.48	17.14
food_topics	0.00	1.62	1.24	2.12	0.00	0.16	2.44	3.90	0.76	1.69	0.00	4.08	100.00	0.00	5.71
panic_buying	0.00	0.11	0.05	0.03	0.00	0.00	0.24	0.00	0.10	0.00	0.00	0.41	0.00	100.00	0.00
food_waste	0.00	0.26	0.12	0.00	0.00	0.00	0.61	0.35	0.10	0.19	0.00	0.24	0.51	0.00	100.00

40-50% 30-40% 20-30% 15-20% 10-15%

Source: author's calculations

Table 41 Cross Tabulation Summary

	Mean_likes_count	Cross classified with how many other categories
Adjust_opreation_support	23.2	0
Hvsl	22.4	5
Emergency_response	8.5	8
DT	6.6	1
PPE	6.2	2
Goods_service	6.1	1
Hygiene_disinfect	5.7	2
Food_topics	4.5	0
Gsp	4.5	14
Social_activity	4.2	0
COVID_workers	4.2	4
Medical_frontline_worker	4.2	3
Isolate_quarantine	4.0	2
Treatment_test	3.7	2
Shutdown_close	3.6	8
Food_waste	3.5	0
Physical_distance	3.3	10
Recover_reopen	3.2	21
Supply_chain	2.8	11
Mental_health	2.3	0
Information_resource	2.1	9
HS_guidance	1.7	0
Panic_buying	1.7	0
Employment	1.6	0
Misinformation	1.4	0
Cyber_security	1.2	0
Apologize	0.9	2

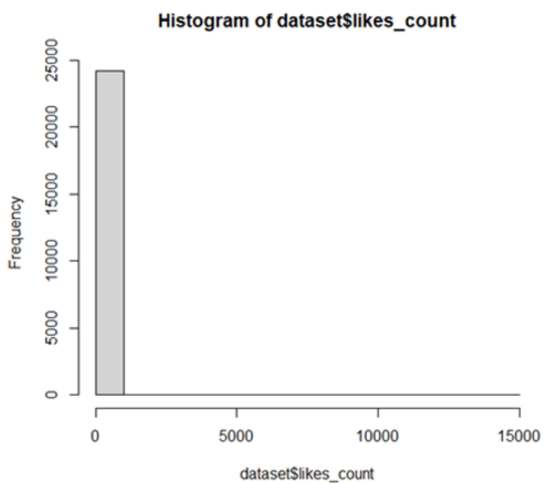
Source: author's calculations

10.5 Models Comparation and Selection

I fitted several models to decide the appropriate model for the dataset.

10.5.1 OLS Model

From the histogram, we can see that the likes_count data are discrete and can only be zero or positive integers. Likes counts bunch up on the left side of the range, creating a distribution with a positive skew. To deal with skewness and get closer to a normal distribution, I did a log transformation for likes_count. Unfortunately, log transformation did not remove the skewness of the original data. The distribution of log(likes_count+1) is still not normal (Figure 26). OLS requires the response variable to be a continuous quantity without restrictions on its range, whereas count data must have non-negative integer values. Thus, linear regression (Ordinary Least Squares) is not appropriate in this case. Some count data might be approximated by a normal distribution and reasonably modelled with a linear model, but more often, generalized linear models, such as Poisson distribution or negative binomial distribution are better suited in dealing with count data (Lindén & Mäntyniemi, 2011; Rodriguez, 2007; Spiegelman et al., 2020; Walker, 2018).



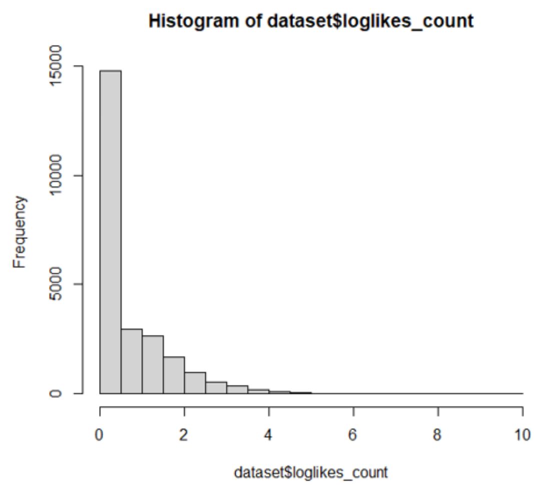


Figure 25 Histograms of Likes_count and Log(likes_count+1)

Source: author’s calculations

10.5.2 Poisson Regression and Negative binomial model

(1) Overdispersion Test

Since the data are discrete with non-negative integer values, Poisson regression model might be suitable to model the relationship among these variables. However, the data is not in the form of a bell curve like in a normal distribution. The variance (8961.023) is much greater than the mean (3.671164), suggesting that this dataset is over-dispersed. The outcome of check_overdispersion() function(performance package (Lüdecke et al., 2021)) also indicates the overdispersion of the Poisson model.

```
# Overdispersion test

       dispersion ratio =      75.910
  Pearson's Chi-Squared = 1837032.166
                p-value =     < 0.001

Overdispersion detected.
```

Figure 26 Overdispersion Test

Source: author's calculations

Negative binomial regression can be considered as a generalization of Poisson regression and can be used for over-dispersed count data. Negative binominal model has the same mean structure as Poisson regression but it has an extra parameter to model the over-dispersion(Ford, 2016; *Negative Binomial Regression | R Data Analysis Examples*, n.d.; *Negative Binomial Regression | Stata Data Analysis Examples*, n.d.; Rodríguez, 2013). Poisson model and negative binomial model comparison results are shown in Table 51.

The rootogram (Kleiber & Zeileis, 2016) of Poisson regression model(Figure 28) also indicates a great deal of underfitting and overfitting. In order to accommodate over-dispersion in the regression model, I decided to choose the negative binomial regression model.

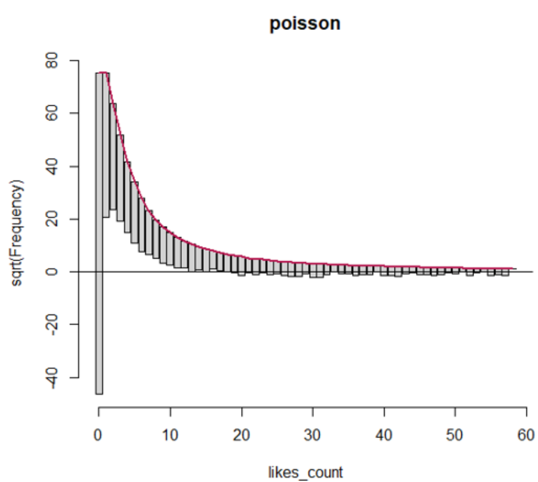


Figure 27 Rootogram of Poisson Model

Source: author's calculations

(2) Zero-inflation Check

I also used check_zeroinflation() to check whether count models are over- or underfitting zeros in the outcome. Zero-inflation is indicated when the amount of observed zeros is larger than the amount of predicted zeros(*Check_zeroinflation: Check for Zero-Inflation in Count Models in*

Performance: Assessment of Regression Models Performance, n.d.). The result also suggests negative binominal model is better than Poisson model.

```
> check_zeroinflation(poisson)
# Check for zero-inflation

   Observed zeros: 14796
  Predicted zeros: 5680
            Ratio: 0.38

Model is underfitting zeros (probable zero-inflation).
> check_zeroinflation(negb)
# Check for zero-inflation

   Observed zeros: 14796
  Predicted zeros: 14966
            Ratio: 1.01

Model seems ok, ratio of observed and predicted zeros is within the tolerance range.
```

Figure 28 Zero-Inflation Check

Source: author's calculations

10.5.3 Comprehensive Visualization of Negative Binomial Model Checks

I decided to choose Negative Binomial model. The following plots provide the check results of negative binomial model assumptions, including collinearity, normality homogeneity, influential observation and normally of residuals. All results indicate this model performs well.

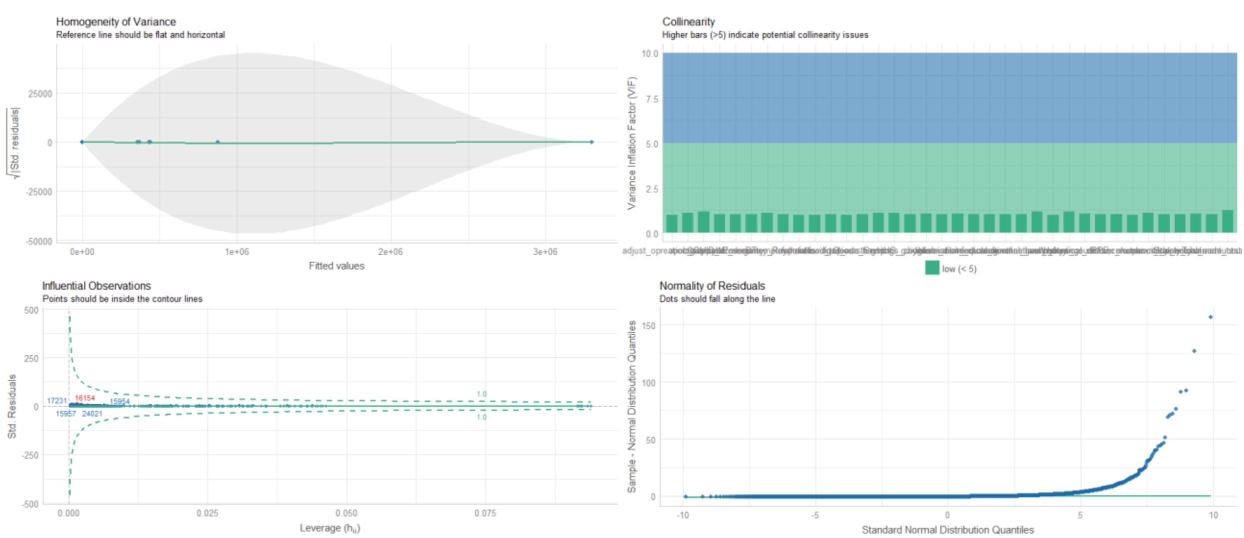


Figure 29 Comprehensive Visualization of Negative Binomial Model Checks

Source: author's calculations

10.6 Negative Binomial Model Results

Two models are presented in Table 42 to test the hypotheses. The first model only includes control variables, and this model shows that the control variables are positive and highly significant, except mentions_count. Model 2 introduces all the focal variables. In Model 2, all control variables are significant.

Table 42 Regression Results

	Dependent variable:	
	likes_count	
	(1)	(2)
compound	0.63^{***}	0.48^{***}
	(0.04)	(0.04)
photos_count	1.06^{***}	1.03^{***}
	(0.03)	(0.03)
hashtags_count	0.12^{***}	0.11^{***}
	(0.01)	(0.01)
mentions_count	-0.04	0.16^{***}
	(0.02)	(0.02)
urls_count	0.63^{***}	0.80^{***}
	(0.03)	(0.03)
lang	0.62^{***}	0.54^{***}
	(0.07)	(0.07)
followers	0.0000^{***}	0.0000^{***}
	(0.0000)	(0.0000)
following	0.0001^{***}	0.0000^{***}
	(0.0000)	(0.0000)
total_social_accounts	0.34^{***}	0.34^{***}
	(0.01)	(0.01)
Emergency_response		-0.13^{**}
		(0.05)
COVID_workers		0.43^{***}
		(0.06)
Medical_frontline_worker		0.42^{***}
		(0.07)
Employment		-0.33^{***}
		(0.10)
Mental_health		-0.03
		(0.13)
PPE		0.49^{***}
		(0.10)
Physical_distance		-0.01
		(0.06)
Hygiene_disinfect		0.24^{*}
		(0.10)
Isolate_quarantine		0.07
		(0.07)

HS_guidance		-0.62***
		(0.13)
Treatment_test		0.21**
		(0.08)
Hvsl		0.64***
		(0.07)
Adjust_opreation_support		4.05***
		(0.32)
Gsp		0.36***
		(0.05)
Recover_reopen		0.07
		(0.04)
Information_resource		-0.35***
		(0.05)
Misinformation		-0.05
		(0.30)
Apologize		-0.97***
		(0.07)
Goods_service		0.57***
		(0.08)
Social_activity		0.30*
		(0.13)
Shutdown_close		0.31***
		(0.05)
DT		0.38***
		(0.07)
Cyber_security		-0.93***
		(0.15)
Supply_chain		-0.04
		(0.05)
Food_topics		0.38***
		(0.11)
Panic_buying		0.002
		(0.46)
Food_waste		-0.53
		(0.38)
Constant	-2.26***	-2.53***
	(0.09)	(0.09)
Observations	24,237	24,237
Log Likelihood	-39,594.79	-39,199.03
theta	0.21*** (0.003)	0.23*** (0.003)
Akaike Inf. Crit.	79,209.58	78,472.07
Note:	* p<0.1; ** p<0.05; *** p<0.01	

Source: author’s calculations

H2-1: There will be more likes when the responses express more concern for workers.
According to Model 2 results, Emergency response is significantly negative(β = -0.13, p <0.005), which is contrary to hypothesis H2-1a. COVID worker (β = 0.43, p <0.001) and Medical worker(β = 0.42, p <0.001) responses are positive and significant in Model 2, supporting H2-1b and H2-1c. Employment (β = -0.33, p <0.001) is negative and highly significant, but Mental health is not significant(β = -0.03, $n.s.$). Thus, hypothesis 2-1d and 2-1e are not supported. In summary, H2-1 is partially supported.

Table 43 H2-1 Results

Hypothesis	Sub-hypothesis	Regression Result	Support Sub-Hypothesis	Support Hypothesis
H2-1: There will be more likes when the responses express more concern for workers.	H2-1a: emergency response tweets are more likely to get likes	Negative, Significant	Not support	Partially support
	H2-1b: COVID-19 workers tweets are more likely to get likes	Positive, Highly Significant	Support	
	H2-1c: medical_frontline workers tweets are more likely to get likes	Positive, Highly Significant	Support	
	H2-1d: Employment tweets are more likely to get likes	Negative, Highly Significant	Not Support	
	H2-1e: Mental Health tweets are more likely to get likes	Not significant	Not Support	

Source: created by author based on regression results

H2-2: Tweets that have mentioned pandemic prevention measures are more likely to earn likes.
Hypothesis 2-2 is somewhat supported. In all sub hypotheses, PPE is positive and highly significant(β = 0.49, p <0.001), which supports the H3-2a. Hygiene_disinfect and Treatment_test are positive and significant(β = 0.24, p <0.1; β = 0.21, p <0.05), supporting the hypotheses H2-2c and H2-2f. Isolate_quarantine, although is positive as H2-2d, is not significant(β = 0.07, $n.s.$). H2-2b and H2-2e are not supported since Physical_distance is negative and not significant(β = -0.01, $n.s.$) and HS_guidance is highly significant but negative(β = -0.62, p <0.001).

Table 44 H2-2 Results

Hypothesis	Sub-hypothesis	Regression Result	Support Sub-Hypothesis	Support Hypothesis
H2-2: Tweets that mentioned health and safety measures are more likely to get likes.	H2-2a: PPE tweets are more likely to get likes	Positive, Highly Significant	Support	Partially Support
	H2-2b: Physical distance tweets are more likely to get likes	Not significant	Not Support	
	H2-2c: Hygiene disinfect tweets are more likely to get likes	Positive, Marginally Significant	Support	
	H2-2d: Isolate and quarantine tweets are more likely to get likes	Not Significant	Not Support	
	H2-2e: Health and safety guidance tweets are more likely to get likes	Negative, Highly Significant	Not Support	
	H2-2f: Treatment test tweets are more likely to get likes	Positive, Significant	Support	

Source: created by author based on regression results

H2-3: There will be more interactions likes when the responses express more concern for consumers.

The results are all in accordance with sub-hypotheses. Hypothesis2-3 is supported.

Table 45 H2-3 Results

Hypothesis	Sub-hypothesis	Regression Result	Support Sub-Hypothesis	Support Hypothesis
H2-3: There will be more likes when the responses express more concern for consumers, except for apology tweets	H2-3a: Apology tweets are less likely to get likes	Negative, Highly Significant	Support	Support
	H2-3b: Social activity tweets are more likely to get likes	Positive, Marginally significant	Support	
	H2-3c: Goods and service tweets are more likely to get likes	Positive, Highly Significant	Support	

Source: created by author based on regression results

H2-4: There will be more interactions likes when the responses express more concern for community.

All four variables are significant, and three of the four results are following the hypothesized direction (adjust operation support: $\beta=4.05$, $p<0.01$; gsp: $\beta=0.36$, $p<0.01$; hvsl: $\beta=0.64$, $p<0.01$).

Table 46 H2-4 Results

Hypothesis	Sub-hypothesis	Regression Result	Support Sub-Hypothesis	Support Hypothesis
H2-4: There will be more likes when the responses express more concern for community.	H2-4a： Tweets mentioning switching or adjusting operation to produce medical supplies are more likely to get likes	Positive, Highly Significant	Support	Mostly Support
	H2-4b: Tweets expressing gratitude and encourage people to stay positive are more likely to get likes	Positive, Highly Significant	Support	
	H2-4c: Information and resources sharing tweets are more likely to get likes	Negative, Highly Significant	Not Support	
	H2-4d: Tweets about helping vulnerable people and community and supporting local community and business are more likely to get likes	Positive, Highly Significant	Support	

Source: created by author based on regression results

H2-5: There will be more likes when the companies discussing hot social topics

Most sub-hypotheses of H2-5 are not supported. Only food_topics is in accordance with hypothesis 2-5d, with a positive and highly significant coefficient ($\beta=0.38$, $p<0.01$).

Table 47 H2-5 Results

Hypothesis	Sub-hypothesis	Regression Result	Support Sub-Hypothesis	Support Hypothesis
H2-5: There will be more likes when the companies discussing hot social topics	H2-5a: Cyber security tweets are more likely to gain likes	Negative, Highly Significant	Not Support	Mostly Not Support
	H2-5b: Food waste tweets are more likely to get likes	Not Significant	Not Support	
	H2-5c: Misinformation tweets are more likely to get likes	Not Significant	Not Support	
	H2-5d: Tweets discussing food topics are more likely to attract likes	Positive, Highly Significant	Support	
	H2-5e: Panic buying tweets are more likely to get likes	Not Significant	Not Support	

Source: created by author based on regression results

Hypothesis 2-7, hypothesis 2-8 and hypothesis 2-9 are not supported by the regression results. Digital_transformation is positive and significant ($\beta=0.38$, $p<0.01$), supporting hypothesis H2-6. Supply_chain is not significant ($\beta = -0.04$, n.s.), which is contrary to hypothesis H2-7. Shutdown_close is positive, with a strong and highly significant coefficient ($\beta=0.31$, $p<0.01$), which is not in accordance with hypothesis H2-8. Recover_reopen, although positive as per hypothesis H2-9, is not significant ($\beta=0.07$, n.s.).

Table 48 H2-6, H2-7, H2-8, H2-9 Results

Hypothesis	Regression Result	Support Hypothesis
H2-6: Digital transformation tweets are more likely to get likes	Positive, Highly Significant	Support
H2-7: There will be more likes when the responses express more concern for supply chain.	Not Significant	Not Support
H2-8: Shutdown responses are less likely to get likes.	Positive, Highly significant	Not Support
H2-9: Recover and reopen responses are more likely to obtain likes	Not Significant	Not Support

Source: created by author based on regression results

10.7 Robustness Check with COVID English Tweets

I conducted negative binomial regression using COVID English tweets to do a robustness check to test the same hypotheses. The results of English tweets (English) and English_French Tweets (En_Fr) are almost the same (See Table 50).

10.8 COVID French Tweets regression

Although English tweets constitute the largest proportion among all the tweets, there might be divergences across different languages. Thus, I expanded the analysis to French.

We can see from the French model (Table 50) that control variables, including photos_count, hashtags_count, and mentions_count, are not significant. In the French model, there are fewer hypotheses supported by the regression results. Hypothesis 2-1 are not supported in French model. Sub-hypotheses H2-1b and H2-1c are not supported (COVID Worker: β=-0.13, n.s; medical_frontline workers: β=0.54, n.s), which are different from the English regression result. Health and safety guidance is positive and significant (β=1.68, p<0.01), supporting H2-2e. Treatment and test hypothesis (H2-2f) is supported in English tweets model, but not supported in French model (β=0.31, n.s). H2-2a (PPE) and H2-2c (hygiene_disinfect) are both supported in English model and French model. Regarding hypothesis 2-3, social activity and Goods and Service are not supported in French model (social activity: β=-1.46, n.s; Goods Service: β=0.11, n.s), which are different from the results in English tweets Model. H2-4a (Adjust operation to support) is highly supported in English tweets model (β=4.07, p<0.01). However, adjust_operation_support is not significant in French model (β=-1.86, n.s). There are no French tweets about misinformation. Food_topics is negative, and highly significant (β=-1.74, p<0.001), not supporting H2-5d. Digital transformation is positive, but not significant (β=0.20, n.s), which is not in accordance with H2-6. H2-7 (Supply Chain) is supported in French model (β=0.45, p<0.01).

Table 49 English and French Regression results

Hypothesis	Sub-hypothesis	English Regression Result	Support hypothesis or not (English)	French Regression Results	Support hypothesis or not (French)
H2-1: There will be more likes when the responses express more concern for workers.	H2-1a: Emergency response tweets are more likely to get likes	Negative, Significant	Not support	Not Significant	Not support
	H2-1b: COVID-19 Workers tweets are more likely to get likes	Positive, Highly Significant	Support	Not Significant	Not support

	H2-1c: Medical_frontline workers tweets are more likely to get likes	Positive, Highly Significant	Support	Not Significant	Not support
	H2-1d: Employment tweets are more likely to get likes	Negative, Highly Significant	Not Support	Not Significant	Not support
	H2-1e: Mental Health tweets are more likely to get likes	Not significant	Not Support	Not Significant	Not support
H2-2: Tweets that mentioned health and safety measures are more likely to get likes.	H2-2a: PPE tweets are more likely to get likes	Positive, Highly Significant	Support	Positive, Highly Significant	Support
	H2-2b: Physical distance tweets are more likely to get likes	Not significant	Not Support	Negative, Marginally significant	Not Support
	H2-2c: Hygiene disinfect tweets are more likely to get likes	Positive, Marginally Significant	Support	Positive, Highly Significant	Support
	H2-2d: Isolate and quarantine tweets are more likely to get likes	Not Significant	Not Support	Negative, Highly Significant	Not Support
	H2-2e: Health and safety guidance tweets are more likely to get likes	Negative, Highly Significant	Not Support	Positive, Significant	Support
	H3-2f: Treatment test tweets are more likely to get likes	Positive, Significant	Support	Not Significant	Not Support
H2-3: There will be more likes when the	H2-3a: Apology tweets are less likely to get likes	Negative, Highly Significant	Support	Negative, Highly Significant	Support

responses express more concern for consumers, except for apology tweets	H2-3b: Social activity tweets are more likely to get likes	Positive, Marginally significant	Support	Not Significant	Not Support
	H2-3c: Goods and service tweets are more likely to get likes	Positive, Highly Significant	Support	Not Significant	Not Support
H2-4: There will be more likes when the responses express more concern for community.	H2-4a： Tweets mentioning switching or adjusting operation to produce medical supplies are more likely to get likes	Positive, Highly Significant	Support	Not Significant	Not Support
	H2-4b: Tweets expressing gratitude and encourage people to stay positive are more likely to get likes	Positive, Highly Significant	Support	Positive, Highly Significant	Support
	H2-4c: Information and resources sharing tweets are more likely to get likes	Negative, Highly Significant	Not Support	Not Significant	Not Support
	H2-4d: Tweets about helping vulnerable people and community and supporting local community and business are more likely to get likes	Positive, Highly Significant	Support	Positive, Highly Significant	Support
H2-5: There will be more likes when the	H2-5a: Cyber security tweets	Negative, Highly Significant	Not Support	Not Significant	Not Support

companies discussing hot social topics	are more likely to gain likes				
	H2-5b: Food waste tweets are more likely to get likes	Not Significant	Not Support	Not Significant	Not Support
	H2-5c: Misinformation tweets are more likely to get likes	Not Significant	Not Support	NA	NA
	H2-5d: Tweets discussing food topics are more likely to attract likes	Positive, Highly Significant	Support	Negative, Significant	Not Support
	H2-5e: Panic buying tweets are more likely to get likes	Not Significant	Not Support	Not Significant	Not Support
H2-6: Digital transformation tweets are more likely to get likes		Positive, Highly Significant	Support	Not Significant	Not Support
H2-7: There will be more likes when the responses express concern for supply chain		Not Significant	Not Support	Positive, Marginally Significant	Support
H2-8: Shutdown and close responses are less likely to get likes		Positive, Highly Significant	Not Support	Not Significant	Not Support
H2-9: Recover and Reopen tweets are more likely to obtain likes		Not Significant	Not Support	Not Significant	Not Support

Source: created by author based on regression results

Table 50 Englsih negb, French negb, English_French negb, English_French Poisson models

	Dependent variable:			
	likes_count			
		negative binomial		*Poisson*
	En	Fr	En_Fr	En_Fr
compound	0.49^{***}	0.27^{*}	0.48^{***}	0.65^{***}
	(0.04)	(0.11)	(0.04)	(0.01)
photos_count	1.10^{***}	0.12	1.03^{***}	0.45^{***}
	(0.03)	(0.10)	(0.03)	(0.005)
hashtags_count	0.11^{***}	-0.04	0.11^{***}	0.08^{***}
	(0.01)	(0.03)	(0.01)	(0.002)
mentions_count	0.16^{***}	0.01	0.16^{***}	-0.21^{***}
	(0.02)	(0.06)	(0.02)	(0.01)
urls_count	0.83^{***}	0.43^{***}	0.80^{***}	0.34^{***}
	(0.03)	(0.12)	(0.03)	(0.01)
followers	0.0000^{***}	-0.0000^{***}	0.0000^{***}	0.0000^{***}
	(0.0000)	(0.0000)	(0.0000)	(0.00)
following	0.0000^{***}	0.0001	0.0000^{***}	0.0001^{***}
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
total_social_accounts	0.33^{***}	0.70^{***}	0.34^{***}	0.32^{***}
	(0.01)	(0.07)	(0.01)	(0.004)
lang			0.54^{***}	0.80^{***}
			(0.07)	(0.02)
Emergency_Response	-0.15^{**}	0.13	-0.13^{**}	0.29^{***}
	(0.05)	(0.12)	(0.05)	(0.01)
COVID_Workers	0.42^{***}	-0.13	0.43^{***}	0.35^{***}
	(0.06)	(0.23)	(0.06)	(0.01)
medical_frontline_worker	0.43^{***}	0.54	0.42^{***}	0.59^{***}
	(0.07)	(0.36)	(0.07)	(0.01)
employment	-0.32^{**}	-0.38	-0.33^{***}	-0.54^{***}
	(0.10)	(0.30)	(0.10)	(0.03)
mental_health	-0.04	0.26	-0.03	-0.14^{***}
	(0.14)	(0.47)	(0.13)	(0.04)
PPE	0.45^{***}	1.37^{**}	0.49^{***}	0.22^{***}
	(0.10)	(0.45)	(0.10)	(0.02)
physical_distance	-0.02	-0.71^{*}	-0.01	-0.14^{***}
	(0.06)	(0.30)	(0.06)	(0.01)
hygiene_disinfect	0.21^{*}	2.11^{***}	0.24^{*}	0.55^{***}
	(0.10)	(0.48)	(0.10)	(0.02)
isolate_quarantine	0.10	-1.34^{***}	0.07	-0.49^{***}
	(0.08)	(0.40)	(0.07)	(0.02)
HS_guidance	-0.73^{***}	1.68^{**}	-0.62^{***}	-0.75^{***}

	(0.13)	(0.60)	(0.13)	(0.04)
Treatment_test	0.22**	0.31	0.21**	0.37***
	(0.08)	(0.29)	(0.08)	(0.02)
hvsl	0.64***	0.74**	0.64***	1.13***
	(0.07)	(0.28)	(0.07)	(0.01)
adjust_opreation_support	4.07***	-1.86	4.05***	1.75***
	(0.33)	(1.30)	(0.32)	(0.03)
gsp	0.36***	0.37*	0.36***	-0.12***
	(0.05)	(0.17)	(0.05)	(0.01)
recover_reopen	0.06	-0.06	0.07	-0.09***
	(0.04)	(0.13)	(0.04)	(0.01)
information_resource	-0.35***	-0.19	-0.35***	-0.35***
	(0.05)	(0.14)	(0.05)	(0.01)
Misinformation	-0.05		-0.05	-0.11
	(0.30)		(0.30)	(0.10)
apologize	-0.97***	-0.95***	-0.97***	-1.30***
	(0.07)	(0.28)	(0.07)	(0.03)
Goods_Service	0.58***	0.11	0.57***	0.49***
	(0.08)	(0.25)	(0.08)	(0.01)
social_activity	0.34*	-1.46	0.30*	0.23***
	(0.14)	(0.81)	(0.13)	(0.03)
shutdown_close	0.30***	0.15	0.31***	0.07***
	(0.05)	(0.14)	(0.05)	(0.01)
DT	0.41***	0.20	0.38***	0.66***
	(0.07)	(0.21)	(0.07)	(0.01)
cyber_security	-0.96***	-0.74	-0.93***	-0.83***
	(0.16)	(0.86)	(0.15)	(0.06)
Supply_chain	-0.06	0.45*	-0.04	-0.14***
	(0.05)	(0.18)	(0.05)	(0.01)
food_topics	0.43***	-1.74**	0.38***	0.20***
	(0.12)	(0.54)	(0.11)	(0.02)
panic_buying	0.08	-36.02	0.002	-0.05
	(0.48)	(47,453,133.00)	(0.46)	(0.16)
food_waste	-0.50	-0.72	-0.53	-0.31***
	(0.41)	(1.17)	(0.38)	(0.09)
Constant	-1.97***	-2.74***	-2.53***	-1.89***
	(0.06)	(0.29)	(0.09)	(0.03)
Observations	22,907	1,330	24,237	24,237
Log Likelihood	-37,026.22	-1,945.40	-39,199.03	-148,698.50
theta	0.22*** (0.003)	0.67*** (0.05)	0.23*** (0.003)	
Akaike Inf. Crit.	74,124.43	3,960.80	78,472.07	297,470.90
Note:				*p**p***p<0.001

11. Discussion

11.1 Implications for Research

Already the data exploration provides some insights into how companies have responded to the emergence of COVID-19. As noted above, this study found that the Tweet frequency and hashtags usage were aligned with the timing of the pandemic situation and relevant government responses: in March, April and May, the numbers of tweets are higher than in other periods. It is unclear why the number of tweets started to decline from April. One possible explanation is that most people tend to have more discussions regarding a phenomenon when it is novel, but the discussions may slow down as time progresses.

In terms of the sentiment analysis, there is a notable difference between general tweets, for which positive sentiment accounts for the largest proportion, and COVID-19 related tweets, which show notably higher prevalence of tweets with neutral emotions. The analyses above show that the most common words in neutral tweets are words, such as "case", "vaccine"," disease", "fund" and "government", which are often associated with news articles at that time. This may indicate that companies do not express strong emotions when they are talking about the news, and they may have used their Twitter accounts to provide information updates to their customers.

Another interesting finding in data exploration stage is that some companies that frequently post COVID-19 information on Twitter have a higher number of followers. The data do not permit an analysis of causality in this regard. Their followers can get notifications when these companies release new information. This may indicate that these companies realize the importance of Twitter, and they actively utilize Twitter more extensively as a platform to share relevant information and communicate with their audience.

With regards to identifying topics from the tweets, the analyses above show that topic modeling and the analysis of unigrams and bigrams can highlight some of the topics companies address, but these methods fail to represent the breadth and diversity of responses categories well. In contrast, the inductive, manual development of keywords, which also integrates the keywords and phrases from the unigrams, bigrams and topic modelling results, is shown to be more suitable in this context. The final keyword list is shown to have little overlap between categories and is well aligned with both the results from the web site analysis and the Statistics Canada conceptualization. At the same time, it provides additional detail beyond these other data sources, which the following regression analyses showed to be important in analysing differing levels of user engagement.

This research shows that company's responses can be identified from web content and tweets. By doing both web and Twitter analyses, more comprehensive company's responses can be gained and also a logical structure that shows the high-level responses categories and detailed sub-responses can be created. Compared with the website result, the Twitter analysis result shows more detailed and broader range of responses. Researchers can adopt a similar method to track company' responses and public reactions. Depending on what data researchers can collect and their research objectives, researchers can conduct different analyses. Web data may be better suited to investigate more general responses, such as protection / precautions, communications, and operations. With Twitter data, researchers can investigate more detailed level responses. For example, researchers can investigate subcategories such as PPE, physical distance, hygiene measures, and isolation when the research focuses on health and safety measures. Researchers can also choose the responses they are most concerned about to explore, or create new categories by combining some secondary responses to carry out their own research.

The findings also show that companies cannot expect uniform user engagement simply by referencing COVID-19 in their posts, but users react differently to messages, e.g. relating to worker health and safety, apologies for late reply and shut down notification. Also, there exist divergences across English and French. For example, switching or adjusting operation in English tweets has a large, positive coefficient, but in French tweets, the coefficient is negative. Different results of French and English tweets regression remind researchers to make additional efforts to understand how companies' posts may be interpreted in different languages and cultures.

This study focuses on the agri-food industry. The results show that companies in the agri-food sector discussed some special topics, such as panic buying, foreign and seasonal temporary workers, food security, food security, food safety, food justice, food sovereignty, food literacy, and the future of the food industry. Other responses, such as health and safety measures, may be adopted by other companies and industries as well. It might be interesting to compare the results of different industries. Consumers may be more sensitive when it comes to information from agricultural food companies. As these products are consumed by consumers, their safety concerns may increase. This study may produce more results than other industries, in which consumers have less concerns and products are less likely to harm them.

11.2 Implications for Practice

11.2.1 Social Media and Business

Twitter is the most corporately used social media platform among all the social media platforms and is an excellent venue for businesses to connect instantly with consumers, stakeholders, and other company supporters (Holt, 2016; Kirtiş & Karahan, 2011; Owen, 2021; Sree Sreenivasan, 2021). Companies use Twitter to report the company's news, including product launches and promotional activities and interact with followers by soliciting feedback through questions and open discussions (Kirtiş & Karahan, 2011; Schroeder, 2013). Twitter provides valuable market research for businesses, allowing businesses to track the movements of their competitors, understanding the current interests of consumers, or finding experts who are tweeting about issues of interest to their business (Kerry, 2014; Kirtiş & Karahan, 2011; Schroeder, 2013).

Canadian agriculture and agri-food sector is a modern, integrated, and quickly growing sector of the Canadian economy. For Canada to remain competitive both in domestic and international agricultural markets, its performance must keep up with trends, which may be enhanced by using social media (Kerry, 2014). The agricultural industry can use social media to build strong connections among consumers, stakeholders, employees and the general public by sharing technology, engaging and relevant information (Kerry, 2014). In the United States, agriculture organizations, such as the AgChat Foundation and the American Farm Bureau Federation, have encouraged individuals within the agricultural community to connect communities through social media platforms (Kerry, 2014). Farmers are using social media to share their farming stories, provide product updates, answer consumer questions, explain agriculture misconceptions and fears, and promote their products (Areg Bagdasarian & Tamehiro, 2010; Kerry, 2014). Also, there is a pressing need to exploit social marketing to understand attitudes, perceptions, and barriers that influence the behaviour change of consumers and the agri-food industry (Galanakis et al., 2020, 2021).

With the increasing adoption rate of social media, the public turns to the internet to learn details in a crisis. In this study, there are around 200 companies post more than 20 COVID-19 tweets in 2020, and most of them are large companies or organizations in agriculture sector. Some companies, especially small agri-food companies, do not often use social media or websites. They may not yet fully understand what social media is and how it can assist them in creating participants' engagement. This study demonstrates that the usefulness of social media during crisis. Companies can consider embracing the social media and letting their voice being heard.

11.2.2 Tweets Content

Public users express positive attitudes towards most prevention and protection measures. However, health_safety guidance has a negative effect on likes_count. There reason might be some measures, such as not accepting cash, limiting store capacity, and tracking contact, restrict people's movement, causes inconvenience and lead to privacy issues. Emergency response is also negatively associated with the probability of getting likes. There are indeed some debates and criticisms on the arrangement and implementation of emergency response. Since the outbreak of COVID-19, there are various emergency responses programs and benefits. Among them, Canada Emergency Response Benefit (CERB) was designed to provide income support for people who lost their job because of the national quasi-quarantine. However, many contract workers, part-time workers, students and elderly people in need are not eligible to the program (Ibbitson, 2020). Additionally, some emergency benefits application process is unclear, and people feel confused about where they should go and where they should apply. Transferring between programs is also a messy process (Molko, 2020; Slaughter, 2020). Details surrounding some programs, such as CERB and Employment Insurance(EI), are not clear (Evans, 2020). Many Canadians are confused about the payments they are receiving and frustrated at being unable to ask their questions over the phone. Also, some people start to worry that they may face a new round of financial anxiety when the emergency benefits end (Evans, 2020; Government of Canada, 2019; Ibbitson, 2020; Vessey, 2020).

Information and resources sharing shows negative relationship with likes. Information overload might be one of the reasons (Rathore & Farooq, 2020). Companies may need to avoid sending too much information and not make their audiences overwhelmed. Crisis created a need for information. Companies may need to provide essential information and assistance to mitigate the crisis. Crisis information needs to be shared in a timely and accurate manner.
During crisis, companies can use social media as the primary tool for updates. They can use social media for updates in crisis responses. The information on companies' business hours changes, health and safety measures reporting confirmed cases, goods and service changes can help customers to plan their activities in advance.

Companies can communicate with compassion, concern, and empathy and their communication strategies can demonstrate genuine concern for the situation. Companies can express empathy and support to the people who are most affected by the crisis. Tweets about caring and supporting workers are more likely to gain likes. Audiences prefer to see content about supporting and helping vulnerable people, communities, and local businesses. Expressing positive and optimistic emotions, such as encouraging people to stay positive and stay strong, are also more likely to obtain likes. Companies organize or recommend activities that customers can do during quarantine, such as cooking, baking, and gardening. Businesses can maintain bonds with their customers through cooking classes and recipe sharing. These activities also provide entertainment to customers' quarantine life.

Switching and adjust operation has a large coefficient (4.05). People love to see content about companies' social responsibility, especially adjusting operation or production to produce medical supplies, such as hand sanitizer. Such actions can be present in the communication, building a positive image, and consequently bringing returns in sales, brand value, and credibility, during and after the pandemic (Batista et al., 2020; Edelman, 2020).

Companies can ensure consumer confidence by focusing on actions that demonstrate their efforts to continue serve their customers and maintain operation. Customers like to see content on customers goods and service information, such as delivery, and pick up services. Many companies and organizations are aware of the importance of digital transformation, and audiences are interested in the digital transformation changes that companies have made, such as utilizing online platforms. However, digital transformation also brings digital risks. Cyber security is a growing challenge around the world. As remote work becomes a new normal, organizations are realizing that the security environment has dramatically changed. Senior leadership needs to be able to trust that their teams have secured systems for remote work. Customers need to trust that their data is protected (Hanspal, 2021). Employees need to trust that there are systems in place to support them. Companies should not only just highlight the risks, but also need to provide detailed and practical measures to build security environment.

Due to significant volumes of calls and e-mails and higher demand for goods or services, it is taking longer than usual for companies to respond to customers. Companies express their apologies to customers for not replying in time or delayed orders. This kind of content is not likely to gain likes since it indicates companies' operation vulnerabilities. Companies may need to improve their adaptability and resilience to respond to external changes quickly and serve their customers better.

11.2.3 Tweets in Different Languages

Based on the regression analysis, this study provides some suggestions for different language tweets (Table 51). If companies plan to release the same content in French and English, they can post tweets more about PPE and hygiene measures, expressing gratitude, and supporting local, vulnerable communities and people. Suppose companies have enough time and effort and are willing to publish different content for audiences in different languages. In that case, they can consider tweeting more social responsibilities content in English and posting more content about PPE and hygiene measures in French. Both English and French tweets may consider avoiding or reducing posting content about offering apologies. The business leaders and policy developers need to understand people's timely reactions during the pandemic to ensure the information they post and the measures they adopt move in the right direction to provide services and valuable information to the audience.

Table 51 Responses Guideline

Response	English	French	English and French
Emergency response	👎		
COVID-19 workers	👍		
Medical or frontline workers	👍		
PPE	👍	👍	👍
Physical distance		👎	
Hygiene disinfect Measures	👍	👍	👍
Isolate and quarantine		👎	
health and safety guidance	👎	👍	
Treatment and test	👍		
Apology	👎	👎	👎
Social activity	👍		
Goods and service	👍		
Adjust operation	👍		
Express gratitude and encourage people to stay positive	👍	👍	👍
Sharing information and resources	👎		

Help/Support vulnerable people and community	👍	👍	👍
Supply chain		👍	
Shutdown	👍		
Recover and reopen			
Digital Transformation	👍		
Cyber security	👎		
Food topics	👍	👎	

Note: created by author based on regression analysis. 👍 means recommend posting, 👎 means not recommend posting

12. Limitation and Future Research

I have identified some limitations in this study.

12.1 Data limitations

The real-time posting of tweets is both a strength and a weakness. A strength is that it captures what is happening at the time, but a weakness is that tweet content can evolve very quickly (Duggan et al., 2015), thus requiring constant monitoring of posts. As I used only a static snapshot of data in our analysis, I could not fully capture the dynamic nature of engagement on social media platforms. Some of the posts I analyzed might have received more likes and comments after I downloaded the data, which might have caused biases in my analysis.

In addition, due to time constraints, my research is mainly focused on 2020. In 2020, the situation of COVID-19 was uncertain and kept changing, recover and reopen plans or activities were interrupted several times. There are more recovery and reopen good news in 2021. I may conduct research on 2021 tweets as well.

There are only 1330 French COVID tweets in this study, far fewer than the English dataset. In order to compare the public reaction to different language tweets better, I plan to collect more French tweets.

12.2 Keywords Completeness and Automated Approach Limit

A further limitation is the incompleteness in the keywords list in my study. Even though I utilized several methods, including external resources, manual checking tweets, several round discussions to grow and revise the keyword list, there may still be some keywords related to COVID-19 that have not yet been collected.

I used python code to annotate the tweets. A strength is that code processes a vast amount of data much faster than human methods. However, using code to annotate tweets is a potential weakness since it may not perform as well as human curation. Misclassification may exist.

12.3 Generalizability of Findings

This research only uses data of companies and organizations listed in Food Convergence and Integrity (FCI) project database. In future, similar research can be conducted for companies that are in other industries. Also, more social media platforms should be incorporated in future work, such as Facebook, Instagram, and LinkedIn.

12.4 Proxy for User Interaction and Engagement

Due to the data collection limit, I only collected reliable likes count data. Only using the number of likes might not be the best proxy for user interaction and engagement. As I mentioned in the literature review part, user engagement can be measured using different ways and can even use different indicators to represent engagement phrases. In the future, I intend to run the model with replies and retweets count if these data can be collected. Also, if public replies can be collected, I can analyze replies text to get more insights, rather than focusing on the numeric variables (likes count, retweets count, replies count).

Many researchers mentioned that COVID-19 is a catalyst for resilience (Cheema-Fox et al., 2020; Gyimah, 2020; Heinonen & Strandvik, 2020; Lee & Trimi, 2021). Discussions on how to build and improve resilience have attracted more and more attention. Companies have displayed various resilient responses during COVID-19. From the regression analysis results, I found that digital capacity or presence (total_social_account) positively affects likes count. It would be interesting to investigate the relationship between companies' digital presence and resilient responses.

13. Conclusion

This research aimed to identify company's responses in the context of COVID-19 and investigate the relationships between corporate responses and their reception among social media users. This study demonstrates the possibility of capturing a broad range of corporate responses by analyzing web-based data. The methods and results of the work presented in this study will be of value to researchers and businesses, and policy developers, both relating to COVID-19 and future disruptions. Business developers and policymakers can use a similar method to track companies' responses and public reactions. To better understand public reactions to different responses, I investigated various types of responses that have a potential relationship with the likeability of tweets. This research shows that some responses are more likely to attract public attention and gain positive feedback. Some practical suggestions are provided based on the analysis results. These suggestions may help companies adjust and improve their communication messages conveyed through public outlets (websites and social media posts).

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Appendix A

Table A 1 Topics of Papers Published on Twitter Analysis

Author (Year)	Predicting crimes	Stock market trends	Election	Disaster & Crisis	Misinformation Propagation	Public Health/Disease Outbreaks
Chen et al. (2015)	✓					
Gerber(2014)	✓					
Grover et al.(2019)			✓			
Ruan et al.(2018)			✓			
Kabir & Madria, (2019)				✓		
Buntain et al.(2016)				✓		
Earle et al.(2011)				✓		
Hirata et al.(2018)				✓		
Sebastian et al.(2019)				✓		
Zou et al.(2019)				✓		
Baer (2012)				✓		
Southwell et al.(2019)					✓	
Oyeyemi et al.(2014)					✓	✓
Dela Rosa &Ellen(2009)						✓
Sinnenberg et al (2017)						✓
Eysenbach (2009)						✓
Chew &Eysenbach (2010)						✓
Hagen et al. (2018)						✓
Liang et al. (2019)						✓
Bollen et al (2011)		✓				
Ruan et al.(2018)		✓				
Imran et al.(2016)				✓		
Carley et al.(2016)				✓		

Cheong & Lee, 2011(Cheong & Lee, 2011)				✔		
P. Earle et al., 2010(P. Earle et al., 2010)				✔		
Takahashi et al., 2015(Takahashi et al., 2015)				✔		
Chatfield et al., 2013(Chatfield et al., 2013)				✔		
Castillo, 2016(Castillo, 2016)				✔		
Bondielli & Marcelloni, 2019(Bondielli & Marcelloni, 2019)					✔	
Inuwa-Dutse et al.2018(Inuwa-Dutse et al., 2018)					✔	
Bovet & Makse, 2019(Bovet & Makse, 2019)					✔	

Source: created by author

Table A 2 Papers published on COVID-19 Twitter Analysis

Author (Year)	Time Period	Tweets Number	keywords	Topic Model	Geospatial	Sentiment	Social Network	Validation
Franco-Riquelme and Ordieres-Meré (2020)	2019-12-31 to 2020-05-04	23,221	✔					
Chen et al. (2020)	2020-01-21 to 2020-03-21	123,000,000	✔					
Shanthakumar et al. (2020)	2020-03-14 to 2020-03-24	530,206	✔	✔		✔		✔
Sharma et al. (2020)	2020-01-23 to 2020-05-07	84,345	✔	✔				
Abd-Alrazaq et al. (2020)	2020-02-2 to 2020-03-15	2,800,000	✔	✔		✔		
Ordun et al.(2020)	2020-03-24 to 2020-04-09	23,830,322	✔	✔			✔	
Jahanbin, et al. (2020)	2019-13-31 to 2020-02-06	364,080			✔			
Banda, et al(2020)	2020-01-01 to 2020-04-04	30,990,645	✔					
Medford, et al (2020)	2020-01-14 to 2020-01-28	126,049	✔	✔		✔		✔
Singh, et al (2020)	2020-01-16 to 2020-03-15	2,792,513	✔	✔	✔			
Schild(2020)	2019-11-01 to 2020-03-22	222,212,841	✔	✔			✔	

Ahmed et al. (2020)	2020-04-13 to 2020-04-20	22,785						
Yum (2020)	2020-04-16 to 2020-04-22	2,775				✓		
Lamsal (2020)	2020-04-24 to 2020-07-17	310,000,000	✓		✓	✓	✓	
Hosseini et al.(2020)	2020-03-13 to 2020-04-19	530,249		✓				
Man et al.(2020)	2020-03-20 to 2020-04-19	902,138	✓	✓	✓	✓	✓	
Woo et al.(2020)	2020-02-29	43,832 users and 78,233 relationships					✓	
Gruzd and Mai (2020)	2020-03-8 to 2020-04-09	99,039					✓	
Wasim et al.(2020)	2020-03-27 to 2020-04-04	10,140					✓	

Source: created by author

Appendix B

Table B 1 Brief Summary of Data Mining Process (CRISP-DM)

Research Process	Purpose	Steps	Part
Data Understanding	Collect and get familiar with the data	Web scraping and web analysis	Part 1 Web Data
		Twitter scraping	Part 2 Twitter Data
Data Preparation	Transform the data into a dataset that can be used as input to modelling techniques	In my research, these two steps are intertwined. The order of steps is: • Clean data • Twitter analysis • Tweets Annotation • Create variables • Analysis	
Modeling/ Analysis	Apply modeling techniques		
Evaluation	Validate results	Results validation includes web data, twitter data validation and model evaluation	Part 3 Validation/Evaluation

Source: created by author

Appendix C

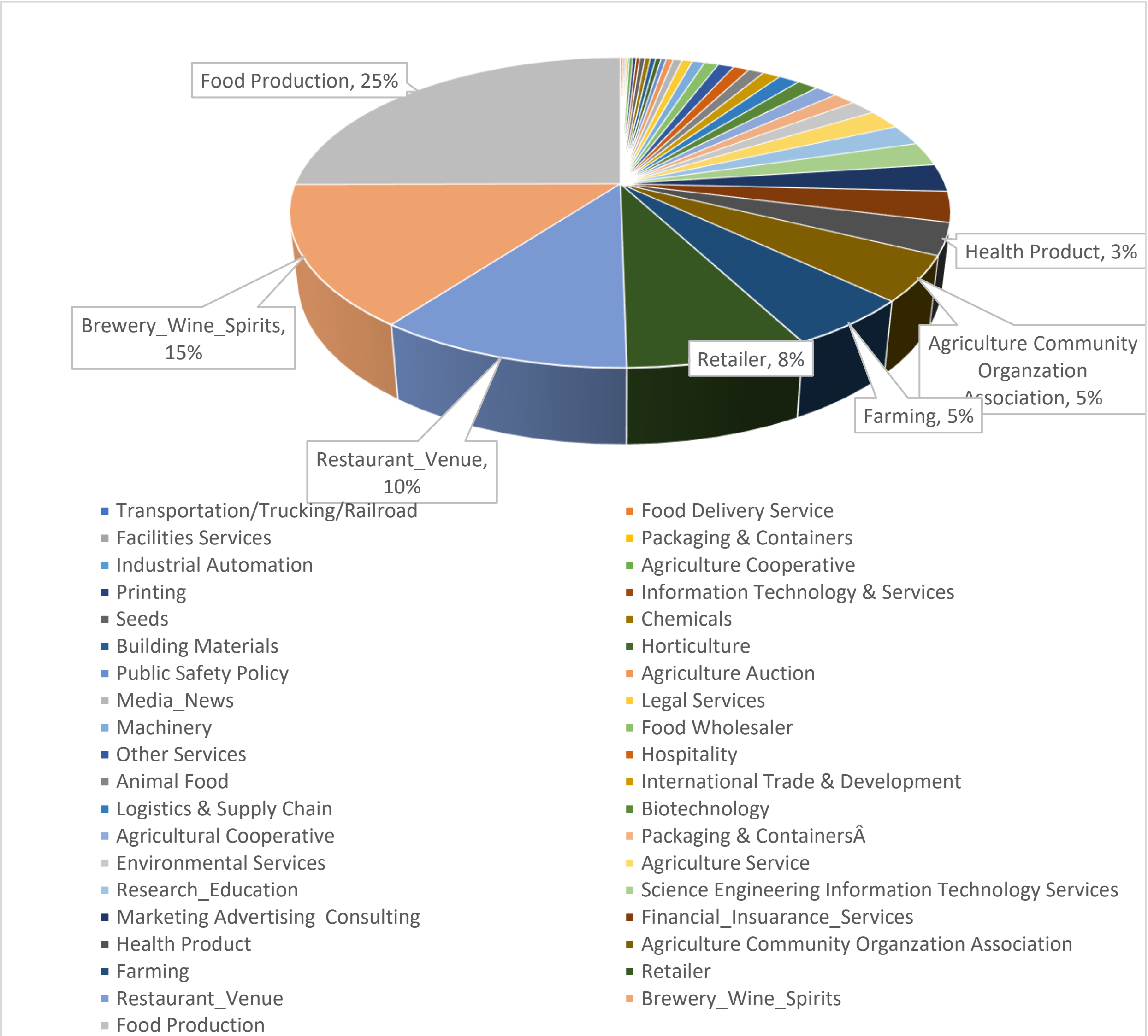


Figure C 1 Industry Distribution

Source: created by author

Figure C 2 Original Tweets

Table C 1 Original Tweet Example

user_id	username	name	tweet
8.37E+17	wearekerry	Kerry Taste & Nutrition	More home cooking has led to an increased awareness of #FoodWaste. Here's a roundup of clean label solutions that can extend product shelf life. #FoodIndustry https://t.co/jgtTS4Mrxm

Figure C 3 Reply Tweet Example

Table C 2 Reply Tweet Example

username	name	tweet	mentions	reply_to
wearekerry	Kerry Taste & Nutrition	@FriendsofOBCC @KING5Seattle @usbank We are proud to support @seattlechildren and their mission to provide quality comprehensive healthcare with dignity for underserved children and families. #NourishingLife	[{'screen_name': 'seattlechildren', 'name': "seattle children's", 'id': '16115979'}]	[{'screen_name': 'FriendsofOBCC', 'name': 'Friends of OBCC', 'id': '1200496219501428736'}, {'screen_name': 'KING5Seattle', 'name': 'KING 5 News', 'id': '19430999'}, {'screen_name': 'usbank', 'name': 'U.S. Bank', 'id': '15577098'}]

Figure C 4 Retweet Example

Table C 3 Retweet Example

username	name	tweet	mentions	user_rt
mb_cropalliance	Manitoba Crop Alliance	RT @Cereals_Canada: @mb_cropallianc	[{'screen_name': 'cereals_canada', 'name': 'cereals canada and cigi (technical division)', 'id':	@mb_cropalliance You now have until tomorrow the 22nd! Please

		e You now have until tomorrow the 22nd! Please go and check out the survey!	'3282629497'}, {'screen_name': 'mb_cropalliance', 'name': 'manitoba crop alliance', 'id': '1133050860227977216' }]	go and check out the survey!

Note: the number of retweets refers to the original post not how many times company's retweet has been retweeted.

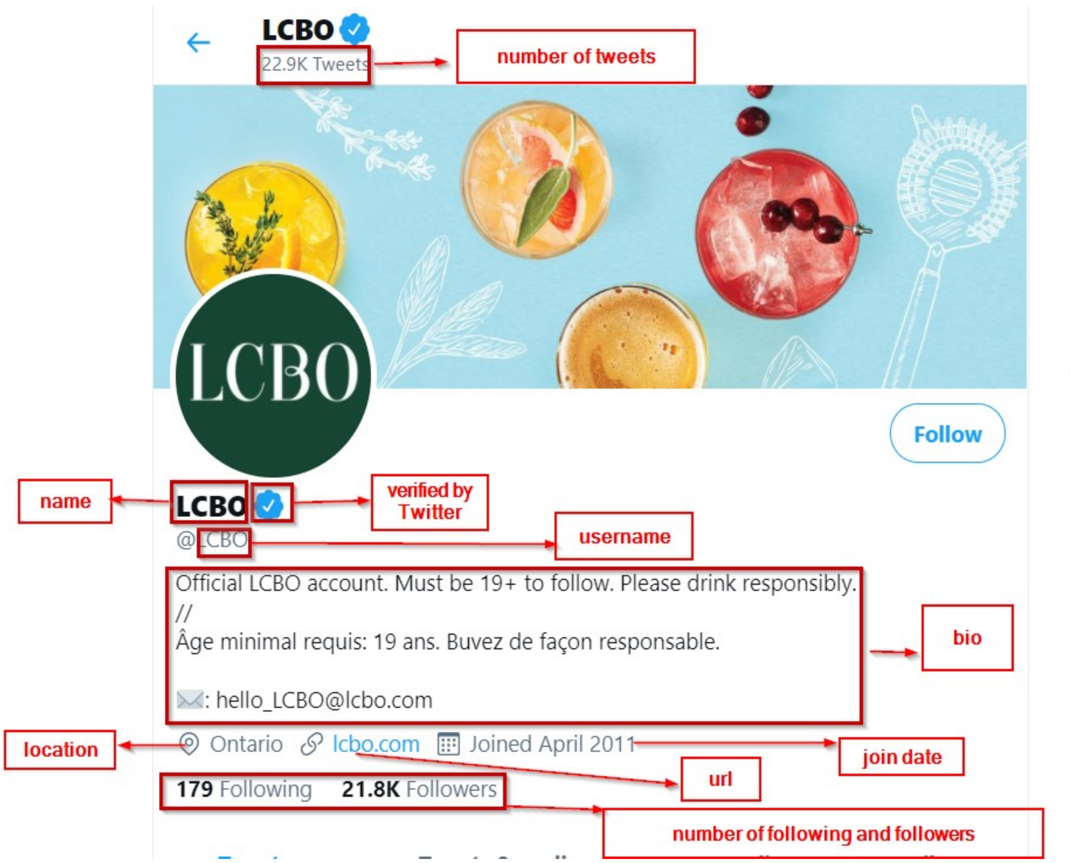


Figure C 5 Profile Example

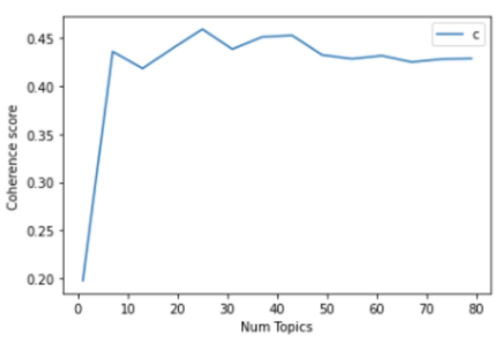
Appendix D

Table D 1 Tweet Translation Example

French Tweet	English Tweet
Les nouveaux arrivages du jour sont des mieux cotés! Apprenez-en plus sur les notes et découvrez notre sélection de plus de 90 vins, seulement au rayon Vintages de la LCBO. Découvrez nos nouveautés ici: https://t.co/2HVmrIP8RZ	Today's new arrivals are top rated! Learn more about ratings and browse our selection of over 90 wines, only in the LCBO Vintages section. Discover our new products here: https://t.co/2HVmrIP8RZ

Table D 2 Tokenization and lemmatization Example

Tweet	Clean tweet	tokens	tokens_back_to_text	lemmas	lemmas_back_to_text
Happy Humpday 🐪! Did you know a yawn is a silent scream for gin?! Lucky enough we have 7 different kinds of gin all made in house! Get over your mid week lull with a tasty cocktail from the Compass Distillers Tower Bar! #compassdistillers #bartenderlife #humpday #cocktails https://t.co/6S6gMgLLDj	happy humpday did you know a yawn is a silent scream for gin lucky enough we have different kinds of gin all made in house get over your mid week lull with a tasty cocktail from the compass distillers tower bar compassdistillers bartenderlife humpday cocktails	['happy', 'humpday', 'know', 'yawn', 'silent', 'scream', 'gin', 'lucky', 'different', 'kinds', 'gin', 'house', 'mid', 'week', 'lull', 'tasty', 'cocktail', 'compass', 'distillers', 'tower', 'bar', 'compassdistillers', 'bartenderlife', 'humpday', 'cocktails']	happy humpday know yawn silent scream gin lucky different kinds gin house mid week lull tasty cocktail compass distillers tower bar compassdistillers bartenderlife humpday cocktails	['happy', 'humpday', 'know', 'yawn', 'silent', 'scream', 'gin', 'lucky', 'different', 'kind', 'gin', 'house', 'mid', 'week', 'lull', 'tasty', 'cocktail', 'compass', 'distiller', 'tower', 'bar', 'compassdistiller', 'bartenderlife', 'humpday', 'cocktails']	happy humpday know yawn silent scream gin lucky different kind gin house mid week lull tasty cocktail compass distiller tower bar compassdistiller bartenderlife humpday cocktails




```
Num Topics = 1  has Coherence Value of 0.1975
Num Topics = 7  has Coherence Value of 0.4362
Num Topics = 13  has Coherence Value of 0.4186
Num Topics = 19  has Coherence Value of 0.4395
Num Topics = 25  has Coherence Value of 0.4596
Num Topics = 31  has Coherence Value of 0.4387
Num Topics = 37  has Coherence Value of 0.4515
Num Topics = 43  has Coherence Value of 0.4531
Num Topics = 49  has Coherence Value of 0.4328
Num Topics = 55  has Coherence Value of 0.4286
Num Topics = 61  has Coherence Value of 0.4319
Num Topics = 67  has Coherence Value of 0.4253
Num Topics = 73  has Coherence Value of 0.4284
Num Topics = 79  has Coherence Value of 0.4289
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Figure D 1 Topic Modelling-Number of Topics

Table D 3 Topic Modelling

Topics	Potential Themes
(0, '0.098*"delay" + 0.068*"respond" + 0.054*"dm" + 0.049*"apologize" + ' '0.045*"send" + 0.043*"number" + 0.041*"address" + 0.034*"message" + ' '0.031*"order" + 0.029*"concern"'),	Apologize for late reply
(1, '0.088*"read" + 0.043*"post" + 0.043*"late" + 0.038*"industry" + ' '0.033*"claim" + 0.033*"share" + 0.027*"impact" + 0.024*"blog" + ' '0.023*"story" + 0.020*"article"'),	Share information
(2, '0.143*"work" + 0.122*"time" + 0.046*"day" + 0.036*"continue" + 0.029*"hard" ' '+ 0.025*"bring" + 0.020*"give" + 0.018*"year" + 0.016*"season" + ' '0.014*"move"'),	Continue working
[(3, '0.068*"government" + 0.062*"support" + 0.061*"response" + 0.052*"canadian" ' '+ 0.040*"announce" + 0.033*"federal" + 0.033*"provide" + 0.032*"benefit" + ' '0.027*"learn" + 0.025*"emergency"'),	Government support
(4, '0.067*"people" + 0.050*"test" + 0.035*"week" + 0.035*"case" + ' '0.034*"million" + 0.030*"issue" + 0.028*"learn" + 0.027*"workplace" + ' '0.026*"key" + 0.021*"continue"'),	Covid test
(5, '0.053*"research" + 0.041*"vaccine" + 0.028*"project" + 0.023*"develop" + ' '0.023*"researcher" + 0.021*"lead" + 0.018*"dr" + 0.017*"science" + ' '0.017*"development" + 0.017*"study"'),	Research, vaccine
(6, '0.057*"join" + 0.053*"webinar" + 0.048*"register" + 0.034*"discuss" + ' '0.027*"watch" + 0.027*"expert" + 0.025*"free" + 0.024*"virtual" + ' '0.021*"today" + 0.019*"live"'),	Activities, such as webinar
(7, '0.073*"order" + 0.058*"cancel" + 0.052*"online" + 0.035*"receive" + ' '0.032*"place" + 0.032*"day" + 0.031*"event" + 0.028*"account" + ' '0.020*"stock" + 0.020*"item"'),	Services changes

(8, '0.052*"store" + 0.051*"open" + 0.038*"close" + 0.029*"remain" + ' '0.025*"closure" + 0.023*"hour" + 0.022*"restaurant" + 0.022*"grocery" + ' '0.019*"location" + 0.017*"area"'),	Operation hour changes
(9, '0.189*"food" + 0.055*"supply" + 0.030*"chain" + 0.030*"system" + ' '0.028*"global" + 0.025*"app" + 0.019*"download" + 0.017*"disruption" + ' '0.015*"build" + 0.015*"strong"'),	Supply chain
(10, '0.042*"market" + 0.028*"economic" + 0.027*"economy" + 0.016*"month" + ' '0.016*"trade" + 0.015*"report" + 0.015*"price" + 0.014*"rise" + ' '0.014*"level" + 0.013*"sale"'),	trade
(11, '0.055*"spread" + 0.050*"face" + 0.031*"reduce" + 0.027*"social" + ' '0.027*"mask" + 0.025*"nt" + 0.024*"hand" + 0.019*"protect" + 0.019*"risk" + ' '0.019*"prevent"'),	Reduce virus spread, health and safety measures
(12, '0.085*"fund" + 0.082*"support" + 0.072*"community" + 0.035*"local" + ' '0.034*"team" + 0.026*"partner" + 0.022*"donate" + 0.019*"proud" + ' '0.018*"raise" + 0.017*"launch"'),	Donation, fund raising, support community
(13, '0.102*"business" + 0.059*"program" + 0.047*"grant" + 0.040*"student" + ' '0.039*"apply" + 0.039*"financial" + 0.030*"small" + 0.027*"relief" + ' '0.025*"emergency" + 0.024*"application"'),	emergency response grant or fund
(14, '0.113*"health" + 0.065*"safe" + 0.056*"safety" + 0.038*"ensure" + ' '0.036*"follow" + 0.035*"continue" + 0.029*"important" + 0.028*"measure" + ' '0.027*"public" + 0.025*"good"'),	Health and safety
(15, '0.065*"learn" + 0.058*"change" + 0.044*"company" + 0.037*"crisis" + ' '0.028*"long" + 0.026*"uofg" + 0.024*"impact" + 0.021*"technology" + ' '0.018*"adapt" + 0.017*"great"'),	Operation changes - Technology

(16, '0.045*"home" + 0.030*"stay" + 0.024*"isolation" + 0.023*"quarantine" + ' '0.017*"great" + 0.016*"local" + 0.016*"love" + 0.015*"beer" + ' '0.013*"friend" + 0.011*"summer"'),	Self isolation, quarantine
(17, '0.113*"update" + 0.086*"today" + 0.045*"info" + 0.037*"retail" + ' '0.037*"question" + 0.034*"website" + 0.033*"news" + 0.029*"disease" + ' '0.025*"retailer" + 0.023*"employer"'),	Information update
(18, '0.058*"employee" + 0.032*"family" + 0.032*"create" + 0.027*"share" + ' '0.025*"make" + 0.024*"care" + 0.020*"challenge" + 0.019*"learn" + ' '0.018*"school" + 0.018*"pay"'),	Employee
(19, '0.064*"plan" + 0.059*"production" + 0.055*"start" + 0.052*"demand" + ' '0.048*"current" + 0.038*"temporarily" + 0.035*"meet" + 0.021*"action" + ' '0.021*"product" + 0.019*"rest"'),	Meet customer needs
(20, '0.070*"farmer" + 0.054*"farm" + 0.041*"impact" + 0.035*"cdnag" + ' '0.034*"sector" + 0.028*"agriculture" + 0.025*"ontag" + 0.024*"producer" + ' '0.023*"survey" + 0.021*"canadian"'),	Agriculture sector
(21, '0.064*"business" + 0.064*"information" + 0.062*"find" + 0.048*"resource" + ' '0.046*"check" + 0.038*"risk" + 0.029*"challenge" + 0.024*"solution" + ' '0.023*"organization" + 0.020*"tool"'),	Information, resources for businesses and organizations
(22, '0.079*"worker" + 0.048*"service" + 0.040*"essential" + 0.032*"canadian" + ' '0.029*"provide" + 0.028*"temporary" + 0.026*"step" + 0.023*"travel" + ' '0.022*"healthcare" + 0.019*"access"')]	Essential workers
(23,	Public health

'0.038*"member" + 0.036*"plant" + 0.033*"outbreak" + 0.032*"march" + ' '0.022*"year" + 0.020*"team" + 0.020*"public" + 0.020*"health" + ' '0.019*"state" + 0.019*"facility"'),	
(24, '0.065*"visit" + 0.056*"customer" + 0.050*"experience" + 0.038*"good" + ' '0.036*"high" + 0.030*"call" + 0.029*"result" + 0.025*"increase" + ' '0.024*"relate" + 0.024*"inconvenience"'),	Inconvenience for customers