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Regular Article

Who's To Blame for the COVID-19 pandemic? Perceptions of responsibility during the crisis using text mining and latent Dirichlet allocation

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ABSTRACT

The spread of the contagious COVID-19 virus was quickly followed by an outbreak of explanations and discourses trying to make sense of the crisis. The goal of this paper is to track the changing dynamics of blame attribution and scapegoating in the Canadian population as the COVID-19 pandemic unfolds, with a particular emphasis on the influence of evolving public health measures. The study uses data from a longitudinal survey conducted with a representative sample of 3617 Canadians between April 2020 and May 2021 following a longitudinal design. Latent Dirichlet allocation (LDA), a computational approach to analyze text, was applied to data coming from an open-ended question on who or what should be held responsible for the COVID-19 pandemic. Nine topics were identified, six of which were recurring overtime. Canadians mostly blame distant collectives in the early months of the pandemic, especially China and wet markets. Over time, they increasingly blame local collectives, such as individuals who do not comply with sanitary measures. Blame attribution evolves with the proximity of the threat and the risk of international spread.

1. Introduction

The COVID-19 pandemic and sanitary measures to limit its spread have caused significant worldwide disruptions within a very short period of time. Nearly two months passed between the detection of the first case of COVID-19 virus in Wuhan, China, and the declaration by the World Health Organization that COVID-19 had reached a pandemic status (Labbé et al., 2022). Many nations subsequently instituted sanitary measures to eradicate the virus and limit its spread. Three years later, an estimated 670 million individuals were infected and 6.8 million individuals died (Johns Hopkins University, 2023). The COVID-19 virus also mutated as it spread; several variants of the virus emerged and became dominant strains worldwide.

Alongside the pandemic caused by the virus itself, a pandemic of explanations and causes for the COVID-19 crisis has emerged. When a devastating event occurs, people wonder what happened, why the event happened, and under what circumstances it may happen again. Moreover, in such situations, the amount of information available is often scarce and shifting (Attema et al., 2021). This lack of available information can result in a lack of satisfactory answers, which motivates people to seek for "responsible parties" (Mayor et al., 2012; Strong, 1990). This type of reasoning can lead to a rhetoric of blame (Dionne & Turkmen, 2020; Mayor et al., 2012).

1.1. Research objectives

Recently, there has been a growing interest in understanding shifts in blame attribution as the pandemic evolved (Choli, & Kuss, 2021; Hardy et al., 2021; Nguyen et al., 2021). While some studies have examined the "dynamic" attribution of blame throughout an ever-changing crisis (Choli, & Kuss, 2021; Labbé et al., 2022), there is a significant lack of knowledge about its manifestation and evolution within the population. This study aims to provide analytical insights that may be applicable to a population context. Our paper contributes a focused and contextualized perspective by closely examining the intricate interplay between the dynamics of blame attribution and scapegoating within the Canadian population and the evolving public health measures. We hypothesize that blame attribution follow a pattern where initial blame is attributed

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to distant communities (Mayor et al., 2012; Roy et al., 2020). As the virus spreads, distant attributions decrease and more proximal attribution would increase (Mayor et al., 2012; Roy et al., 2020).

To achieve these objectives, our study uses latent Dirichlet allocation (LDA), an automated approach enabling rapid analysis of extensive textual data by generating latent themes. While blame attribution during COVID-19 has been investigated via interview and open-ended question coding (Hardy et al., 2021), thematic analysis (Choli, & Kuss, 2021; Nguyen et al., 2021) and through cartoon analysis (Labbé et al., 2022), no prior research has delved into the specific methodology we employ. This approach remains relatively unexplored in the social sciences, where most researchers still favor more familiar techniques, such as manual coding (Lindstedt, 2019).

2. Background

2.1. Blame attribution during a pandemic

Blame is a moral judgment that can take two forms: cognitive, meaning a personal and private judgment influenced by emotions or specific information processing, and social, which is a public act expressed in response to norm violations, or the breach of a socially established rule (Malle et al., 2014). Blame attribution is a way to make sense of a crisis and seek "satisfactory answers" for situations that cannot be explained in conventional ways (Barreneche, 2020). The meaning attributed to a devastating event can vary according to the social group, culture and moment in history (Douglas, 1992; Farmer, 2010; Rateau et al., 2021). An event can be attributed to the actions of individuals, can be ascribed to technological development or negatively perceived economic policies, can be interpreted as the result of God's punishment for a wrongdoing, or can be perceived as a coincidence (Farmer, 2010; Douglas, 1992; Rateau et al., 2021).

The cognitive dimension of blame can be comprehended through the Bayesian brain theory, a common approach to understand how individuals process information about the world (Bottemanne et al., 2021). Namely, the brain uses pre-existing knowledge and beliefs to interpret incoming information and generate predictions – a mechanism influenced by the broader social and cultural context (Attema et al., 2021). This dynamic interaction of cognition within the social and cultural aspects produces typifications, where individuals use their general knowledge to construct ideas about the world and simplify the complexity of social life (Kelly et al., 2019). There are times when stocks of knowledge and beliefs held by individuals can be vague, inconsistent, or false (Kelly et al., 2019). In fact, new information can sometimes reinforce false beliefs instead of correcting them, leading to emotional responses such as blame.

Significant insights into how individuals assign blame in various contexts have been derived. Humans have an inherent need to perceive the world as structured and to maintain control over their lives (Joffe, 1999; Gilles et al., 2011; Proulx & Inzlicht, 2012). In circumstances where this sense of control diminishes, individuals may employ compensatory strategies, such as seeking clear and simple interpretations of reality, or resort to scapegoating in order to cope with feelings of helplessness (Joffe, 1999; Malle et al., 2014; Landau et al., 2015). Scapegoating is the transfer of blame, anger or anxiety onto individuals who are not responsible for a negative event, but who are easy targets for attack because of characteristics they possess (Girard, 1986; Jensen, 2007).

Examining blame through the lens of social dynamics and categorization, researchers addressed the notion of perception of "the Other" (Barreneche, 2020; Bucher, 1957; Jensen, 2007; Joffe, 1999; Petersen & Lupton, 2000). Social categorization is the propensity to classify the world into groups based on broad dimensions such as gender, age or ethnicity (Baron et al., 1997). In fact, this disposition goes beyond mere categorization; it involves dividing communities into two primary entities: the ingroup ("us") and the outgroup ("them") (Petersen & Lupton, 2000). The former is perceived positively, while the latter is perceived negatively (Joffe, 1999; Baron et al., 1997; Monson, 2017). Blame is used to assign a form of responsibility and guilt to outgroup members, while maintaining the "positive identity" of the ingroup (Joffe, 1999; Eichelberger, 2007; Bouguettaya, 2022; Ittefaq et al., 2022).

In the realm of social dynamics, blaming and scapegoating are complex and structured processes stemming from pre-existing beliefs and based on social, political and ideological concerns (Joffe, 1999; Nelkin & Gilman, 1988). Scapegoating may serve as a mechanism to restore societal equilibrium, instill a sense of security and reduce the resulting fear in response to a threat (Jensen, 2007). Blame and scapegoating can serve as a mean to protect existing social categories and power relationships (Nelkin & Gilman, 1988; Joffe, 1999; Douglas, 1992) by reinforcing the boundaries between ingroups and outgroups (de Rosa & Mannarini, 2020; Roy et al., 2020). These tactics allow groups in positions of power to divert attention from the real issues, as they have more resources and influence to shape dominant discourses on a social crisis (Jensen, 2007; Joffe, 2011). In this way, blame attribution and scapegoating can reinforce prejudice or discrimination against already marginalized or vulnerable groups in society (Douglas, 1992; Joffe, 2011; Dionne & Turkmen, 2020; Roy et al., 2020; Desmarais et al., 2023). Prejudice against communities such as ethnic minorities, migrants and economically disadvantaged individuals manifests as "prejudgments" leading to negative behavior based on erroneous generalizations towards them (Allport, 1979).

Blame has been a way to explain mysterious, unknown and serious illnesses when medical science is unable to provide definitive explanations (Nelkin & Gilman, 1988). Placing blame defines normality and sets the boundaries for healthy behavior (Douglas, 1992; Nelkin & Gilman, 1988). Assigning blame to outgroups, such as social classes or ethnic groups, is a recurring process that has taken place in various epidemics (Douglas, 1992; Joffe, 1999; Gilles et al., 2011; Eichelberger, 2007; Roy et al., 2020). During the mid-14th century, Jewish communities were accused of spreading the Black Death; many were left untreated and died (Bouguettaya, 2022). Chinese immigrants to North America were often used as scapegoats for smallpox outbreaks during the 19th century (Dionne & Turkmen, 2020; Eichelberger, 2007). More recently, the outbreak of SARS (Severe Acute Respiratory Syndrome) in 2003 was associated with China and the Chinese people, specifically their cultural habits, such as unsanitary markets (Gilles et al., 2011; Abeysinghe, 2016). In the United States, warnings to avoid neighborhoods inhabited by Asians widely circulated (Dionne & Turkmen, 2020; Eichelberger, 2007). Chinese immigrants in New York City were frequently blamed and stigmatized by other residents for the outbreak (Eichelberger, 2007; de Rosa & Mannarini, 2020; Choli, & Kuss, 2021). During both the SARS and avian flu crises, Asians were depicted as communities with "unhealthy" or "unsanitary" cultural and dietary practices (Eichelberger, 2007; Martikainen, & Sakki, 2021).

Marginalized individuals from the outgroup are not the only targets singled out for an illness (Douglas, 1992; Joffe, 2011). Blame attribution shifts as a pandemic unfolds, contingent upon the geographic location of the threat (Mayor et al., 2012; Monson, 2017; Roy et al., 2020). This phenomenon can be explained through the Collective symbolic coping (CSC) model, which provides insight into how groups collectively interpret and navigate emerging threats (Monson, 2017). During the awareness stage of the CSC model, a new threat emerges through media channels, where representations of past diseases may be used to understand the situation (Joffe, 1999; Gilles et al., 2011). Initially, when the threat is deemed geographically distant, blame is often directed on distant parties, such as remote populations and their lifestyles (Abeysinghe, 2016; Mayor et al., 2012; Monson, 2017; Roy et al., 2020). As the threat takes on a global dimension, new blame behaviors emerge (Mondragon et al., 2017), corresponding to the divergence stage. Intensive communication generates multiple interpretations, creating ambiguity and uncertainty about the situation (Gilles et al., 2011). For instance, authorities may be accused of failure to act quickly or sufficiently in the face of the epidemic in order to advance their own agendas (Joffe, 2011; Mondragon et al., 2017). During the convergence stage, a prevailing discourse that reduces uncertainty leads to a shift in blame attribution. When the virus is perceived as an imminent or geographically present threat, blame is often transferred to local parties, such as local residents (Barreneche, 2020). Finally, in the normalization step, the explanation for the event is incorporated in common knowledge (Gilles et al., 2011). In the long term, interpretations could consolidate or evolve towards a more scientifically precise understanding (Gilles et al., 2011).

Blame during the COVID-19 crisis is also dynamic. At the beginning of the COVID-19 pandemic, focus was on China, as it was the first country to establish sanitary measures to limit the spread of the virus (Barreneche, 2020; Choli, & Kuss, 2021). Subsequently, when the virus spread to other countries, attention turned to the responsibility of the population for the spread of COVID-19 (Barreneche, 2020; Labbé et al., 2022). Specific ethnic groups, most notably people of Asian descent, became scapegoats for the COVID-19 pandemic (Martikainen, & Sakki, 2021). Blaming and scapegoating Asians for COVID-19 led to an increase in incidences of racism, discrimination, and violence toward these individuals from the first months of the pandemic (Dionne & Turkmen, 2020; Hardy et al., 2021; Nguyen et al., 2021). However, according to Ferrante et al. (2022), these blaming and scapegoating tendencies should not be generalized to the general population. In fact, while younger people have low and decreasing levels of prejudice, conservatives have high and stable levels of prejudice (Ferrante et al., 2022). Some right-wing politicians and media platforms often referred to COVID-19 as a "Chinese virus" or "Wuhan virus" (Barreneche, 2020; Choli, & Kuss, 2021). According to White (2020), "Verbal and physical attacks on people of Asian descent and descriptions of the disease as "the Chinese virus" are all connected in this long legacy of associating epidemic disease threat and trade with the movement of Asian peoples" (p.1251). Language analysis can provide insight into how blame, scapegoating and prejudice are expressed and how these forms of expression change over time (Strong, 1990).

2.2. Analytic model of language

The study of human language give a deeper understanding into the ways people organize and analyze the world, as well as process and interpret information (de Saussure, 1983). Words that people use in their daily lives can provide a comprehension of their ongoing thoughts and preoccupations. Importantly, when used to characterize an event, words evolve over time, and such change can shed light on how the meaning attached to that event may change (de Saussure, 1983). Words, and their meaning, do not exist in a void. Language is a system of interdependent terms, in which the meaning of words comes from their relationships with other words (DiMaggio et al., 2013).

Natural language processing (NLP) provides a way to study human language using computational techniques (Liddy, 2001). Text mining is a technique that makes it possible to study natural language by extracting extract relevant information and insights from a mass of data, such as texts (Cheng et al., 2022). Topic modeling is a frequently used text mining technique to reduce massive text corpora into simpler and more readily interpretable groups of words, which form latent themes or *topics* (Nelson, 2020). An important feature of topic models is that they include automatic processes for coding very large collections of text (Blei et al., 2003). In fact, the results of topic modeling become more accurate as the collection of texts increases. In addition, topic modeling allow researchers to analyze texts from a different perspective, uncovering new ideas or concepts while remaining grounded in the data (Nelson, 2020). As such, topic models facilitate the analysis of phenomena on a large scale without requiring much more work from researchers. Using automated text analysis methods is crucial to gain insight into the perceptions and experiences of a large number of individuals, especially on novel and evolving issues such as the COVID-19 crisis.

2.3. Latent Dirichlet allocation

Latent Dirichlet allocation (LDA), is the most frequently used topic model (Tudoran, 2018; Westrupp et al., 2022). It provides a practical approach to the challenges of conceptualizing phenomena in the social sciences. Indeed, some of the concepts studied by researchers, such as social status, alienation or anomie, are often complex to define and cannot be directly observed (Boudon, 1962; McCutcheon, 1987). It automatically extracts latent theme (or topics) from texts, making it easier to understand their underlying concepts. The purpose of the LDA algorithm is to group a quantity of words into topics that will be analyzed by researchers.

LDA relies on Bayesian statistics to estimate model parameters. It is a mixture model, since it uses different probability distributions to model the data, namely the Dirichlet distribution and the multinomial distribution (Blei et al., 2003). LDA is also an infinite mixture model, since the Dirichlet distribution can generate an infinite number of possible combinations of topics in documents (Blei et al., 2003). Finally, LDA belongs to mixed membership models, as each document is treated as a mixture of topics and each topic is treated as a mixture of words (Blei et al., 2003).

To estimate the parameters of the LDA model, several hyperparameters are required. Alpha (α) represents the Dirichlet parameter for the distribution of topics in a document (Blei et al., 2003). Beta (β) represents the Dirichlet parameter for the distribution of words in a topic (Blei et al., 2003). The topics are represented by the value K, and the number of Gibbs iteration (N) is used for statistical inference.

LDA reduces researcher bias since the method is data-driven (Westrupp et al., 2022). In addition, it provides a way to organize and understand very large unstructured texts, something manual coding is unable to do due to the magnitude of the task (Cheng et al., 2022). As the number of texts increases, hand-coding becomes more difficult and time-consuming. On the other hand, LDA results are more reliable, precise and detailed as the number of texts increases. It can also detect nuances and relationships in the data that may not be detected by manual coding (Nelson, 2020). Indeed, unlike this method, which employs a theory-driven deductive approach, LDA uses an inductive approach to discover themes out of raw data (Lindstedt, 2019). When compared to other natural language processing methods, LDA has better accuracy and mitigates overfitting (Liu et al., 2011). LDA also has a more precise assignment of documents to topics and provides better word disambiguation in the presence of ambiguous words (Crain et al., 2012).

3. Methodology

3.1. The COVID-19 canadian survey

The data comes from a longitudinal survey entitled "*COVID-19 Canada: The End of the World as We Know It?*" carried out by the Social change, Adaptation and Well-being Laboratory research team from the University of Montréal.[1] The purpose of this survey is to understand social consequences of the COVID-19 pandemic among the Canadian population. Participants of the COVID-19 survey were selected based on established quotas for three sociodemographic variables: age, gender identity and province of residence. They had the option of answering the questionnaire in either French or English. The survey was conducted online and participants who responded to the first survey wave were then invited to respond to future surveys. Articles using data from this survey have previously been published, including Ferrante et al. (2022) and Kil et al., 2023.

[1] The survey wave 1 questionnaire is included in Appendix A. For later waves questionnaires, please contact the research team.

Table 1
Methodological and demographic information.

Survey wave	Sample size *(N)*	Sample size to the open-ended question	Survey Dates	Intervals between survey waves
1	3617	2869	April 6th – May 6th' 2020	2 weeks
2	2282	–	April 21st –May 13th' 2020	2 weeks
3	2369	2230	May 4th – May 25th' 2020	2 weeks
4	2296	–	May 18th – June 10th' 2020	2 weeks
5	2154	1999	June 1st – June 23rd' 2020	2 weeks
6	2116	–	June 15th – July 13th' 2020	2 weeks
7	2072	–	July 13th – August 8th' 2020	4 weeks
8	1871	1778	August 17th – September 13th' 2020	5 weeks
9	1821	–	September 21st – October 19th' 2020	5 weeks
10	1883	1758	November 26th – December 29th' 2020	9 weeks
11	2002	–	April 13th – May 31st' 2021	20 weeks

Among a battery of questions related to people's experiences and attitudes in the context of the pandemic, participants responded to an open-ended question about "Who or what do you hold most responsible for the current COVID-19 crisis?". This question was asked five times (in survey waves 1, 3, 5, 8, 10; see dates and demographic informations in Table 1). The survey was conducted amongst a representative sample of 3617 Canadians at the first survey wave (de la Sablonnière et al. 2020). Of these participants, 2869 individuals responded to the open-ended question. The sample size then decreased at survey wave, as participants had the choice of whether or not to respond to subsequent surveys.

In our study, a participant's open-ended response at a specific survey wave will be considered a single document and will be treated as mixture of topics, and each topic will be treated as a mixture of words.

3.2. Data preprocessing

Before running LDA, the corpus was preprocessed to achieve better data quality and efficiency. French responses were translated into English using *DeepL* and spelling errors were corrected using *Antidote*. Some of the terms were replaced to achieve better standardization of expressions (e.g., *U.S.*, *U.S.A.*, and *America* become *United States*). Some common expressions in our corpora were reduced to single words, such as '*World Health Organization*' which was changed to '*worldhealthorganization*', and '*United States*' which was changed to '*unitedstates*'. Stopwords, punctuation and numbers were removed. All characters were lower-cased and some terms were lemmatized. These steps were realized using *textmineR* and *tidyverse* libraries in the RStudio environment, version 4.0.3 (Jones et al., 2021; Harel et al., Submitted).

3.3. LDA modeling

Following data preprocessing, the next step was to run LDA. We used a script optimized by Harel et al. (Submitted) in RStudio to run the model. Value intervals were specified in the code in order to parameterize alpha (α), beta (β), and the number of Gibbs iterations (N).[2] An optimization method combining the genetic algorithm with the fitness function "coherence" was employed (Harel et al., Submitted). The genetic algorithm selects the most efficient model, and the "coherence" fitness function measures the quality and precision of the model. The coherence of a theme indicates how closely related the words are, and overall coherence assesses the quality of all generated themes (Harel et al., Submitted).

We ran LDA 25 times for each survey wave. Model selection was based on a stability value, that is, the ability to replicate similar distributions when generating other models with LDA (Harel et al. Submitted). To determine the number of topics, we proceeded as follows. First, we ran LDA specifying an interval of values for the number of topics *k*.

[2] The intervals specified for alpha and beta were [0.000001, 1] and the interval specified for the number of Gibbs iteration was [200, 300].

Table 2
Selected models and their parameters for each survey wave and stability score.

Survey wave	Number of topics	Number of Gibbs iteration	Alpha	Beta	Stability score
1	9	226	0.41	0.87	77.33
3	9	239	0.43	0.66	73.80
5	9	262	0.34	0.69	77.75
8	9	294	0.44	0.46	74.87
10	9	299	0.51	0.29	68.20

This interval was set between 7 and 20 topics. Second, the value of *k* with the highest stability was used to determine the final number of topics (Harel et al., Submitted). Finally, we found that the optimal number of topics for each survey wave is $k = 9$, based on model stability. Table 2 shows the parameters of the selected models and stability values. These steps were performed using *textmineR* package and various LDA functions and utilities provided by this code.

4. Results

4.1. Some important events related to the COVID-19 pandemic

Prior to the first survey wave (April 6th to May 6th, 2020), several important events took place. The first case of COVID-19 occurred in Wuhan, China, on December 8th' 2019 (Shangguan et al., 2020). On March 11th' 2020, the World Health Organization declared COVID-19 a pandemic (Labbé et al., 2022). In the second half of March 2020th, the governments of Ontario, Quebec, Manitoba, Saskatchewan and British Columbia decided to close schools, and restrictions on non-essential travel were issued by the Canadian government (Canadian Institute for Health Information, 2020). Moreover, governments in Ontario, Quebec, British Columbia and Saskatchewan closed non-essential businesses and imposed restrictions on gatherings (Canadian Institute for Health Information, 2020).

These events may have shaped blame attribution and scapegoating during the COVID-19 crisis. Before March 2020, most of the major pandemic-related events were taking place in China. Several major decisions by the authorities, such as closing schools, non-essential businesses and borders, as well as restricting gatherings, occurred just before survey wave 1. Compulsory masking and the introduction of the vaccine passport were other health measures introduced as the virus spread, starting at survey wave 8 (Canadian Institute for Health Information, 2020).

4.2. Descriptive statistics

Table 3 presents the mean, median, minimum and maximum number of words for each survey wave. The mean number of words ranges from 3.5 at wave 5 to 4.6 at wave 1. The median also varies between 2 and 3 words. The median value is lower than the mean at each survey wave; this implies that the high number of words in some responses raises the

Table 3
Descriptive statistics of the number of words for each survey wave.

Descriptive statistics	Survey wave 1	Survey wave 3	Survey wave 5	Survey wave 8	Survey wave 10
Mean	4.6	4.1	3.5	4.2	4.2
Median	3.0	2.0	2.0	2.0	2.0
Minimum	1	1	1	1	1
Maximum	75	196	57	78	92
Single word answers	632	540	516	422	419
Total answers	2869	2230	1999	1778	1759

Table 4
Top 10 words per survey wave.

Survey Wave 1	Survey Wave 3	Survey Wave 5	Survey Wave 8	Survey Wave 10
China	Government	Government	Government	Government
Government	China	China	China	People
Chinese	Chinese	Chinese	People	China
Virus	Virus	People	Chinese	Virus
People	People	Virus	Virus	Chinese
Market	No one	No one	No one	Follow
No one	Market	Market	Unknown	No one
Lack	Unknown	WHO	Market	Health
Animal	Lack	Unknown	WHO	Guideline
WHO	Nature	Wet	Spread	Spread

mean. The maximum number of words ranges from 57 words at wave 5 to 196 words at wave 3. Finally, the minimum number of words is 1 at each survey wave. The proportion of responses that include only one word at each survey wave varies between 22.0 % (survey wave 1) and 25.8 % (survey wave 5). The most frequent single word is "China", with a proportion ranging from 9.1 % at wave 1–5.7 % at wave 10. Other frequent single words ("government", "nature", "WHO", "nobody", "chinese", "everyone") have lower proportions, ranging from 0.1 % to 2.4 %.

4.3. Top words mentioned by participants

Table 4 represent the top 10 words mentioned by participants for each survey wave. The World Health Organization (WHO) is sometimes included in the top 10 words mentioned by respondents. The words "government, "China" and "Chinese" are recurrent throughout the survey waves, indicating that they are frequently mentioned when referring to those responsible for the COVID-19 crisis. Data also show an increase of the word "people" in each survey wave. Some new words appear at wave 10, such as "follow", "health" and "guideline". This suggests that participants blame individuals who do not follow sanitary measures in later phases of the pandemic.

4.4. LDA topic proportions and topic summary

Fig. 1 presents LDA topic prevalence for each survey wave. Six topics are recurrent: 1) Chinese Government and WHO; 2) Wet markets; 3) Travel and not closing borders; 4) No one, responsibility ascribed to nature or climate change; 5) Lack of government reaction and slow response; 6) People who do not follow sanitary measures. Tables 5–9 present LDA topics for each survey wave. The top 10 most frequent terms for each topic are presented in these tables. Next, we provide a detailed analysis of the six recurring topics from each survey wave, based on information from Fig. 1 and Tables 5–9 Examples for participants' responses are reported in quotation marks and italics.

4.4.1. Chinese Government and World Health Organization (WHO)

These two entities are most frequently held responsible for the COVID-19 crisis until survey wave 8. The proportion of responses varies between 19.9 % and 30.1 % in survey waves 1 to 5, then decreases to less than 15 % in survey wave 10. The Chinese government and WHO were grouped into one topic, suggesting that participants often mentioned them together: "*Government of China for not containing the virus sooner and advising WHO earlier.*" and "*Containment failure by the Chinese government and slow WHO response*". The Chinese government has also been accused of withholding information about COVID-19: "*The People's Republic of China (government) for withholding information to the public and being deceptive when they finally did admit there was a problem and the ongoing deception.*" WHO is blamed for the lack of promptness to recognize the severity of the virus: "*The WHO not declaring this a pandemic until it spread to the world. This could have been stopped or limited in February.*"

4.4.2. Wet markets

"Wet markets" was one of the most prevalent topics during survey waves 1 to 5, but its prevalence decreases over time. The proportion of responses ranges from 16.3 % to 18.3 % at survey waves 1 to 5, then drops below 15 % at survey waves 8 and 10. Participants referred mostly to animals sold in these places and described them as unsanitary. For example: "*A virus transmitted by bats to small animals (pangolins) hunted for their meat and sold mainly in wet markets in the Hunan region of China, animals that have contaminated the population …*" and "*Wet markets. Animals being kept in conditions that are conducive to the spread of infectious diseases.*"

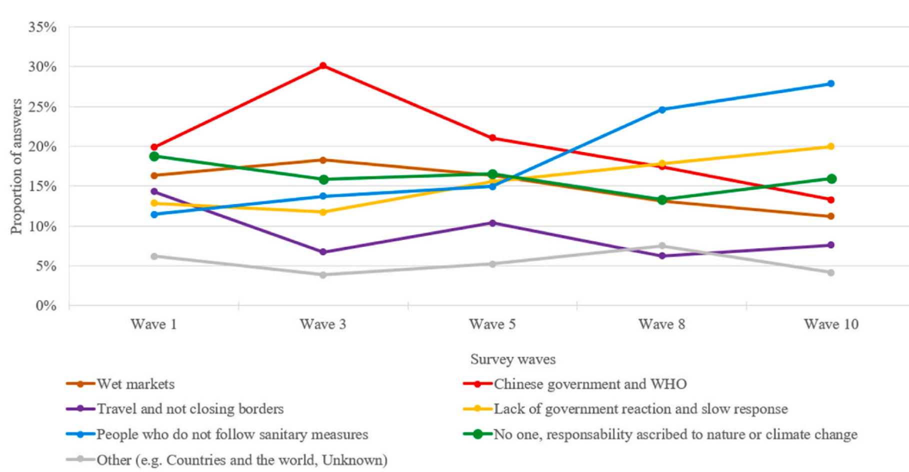

Fig. 1. LDA Topic proportions.

Table 5
Summary of survey wave 1 topics.

Topic	Label	Top 10 Terms
1	Chinese Government, WHO	government, chinese, china, worldhealthorganization, canadian, information, federal, outbreak, hide, chinesecommunistparty
2	Wet markets	china, market, wet, animal, wuhan, live, chinese, wild, food, eat
3	Travel, Not closing Borders	government, china, enough, world, travel, border, soon, spread, virus, act
4	Lack of reaction/slow government response	lack, poor, pandemic, health, response, slow, country, global, china, government
5	People not following sanitary measures	people, take, distance, virus, social, follow, seriously, spread, home, stay
6	No one is responsible	noone, responsible, hold, anyone, crisis, happen, nature, virus, particular, people
7	China not taking the pandemic seriously	china, worldhealthorganization, virus, response, slow, world, government, country, information, pandemic
8	Virus, Nature, Animals	virus, human, animal, nature, bat, eat, china, unknown, transmission, mother
9	Unknown	unknown, virus, country, blame, think, good, know, china, many, canada

Table 6
Summary of survey wave 3 topics.

Topic	Label	Top 10 Terms
1	Chinese Government, WHO	government, chinese, worldhealthorganization, soon, communist, unitedstates, trump, chinesecommunistparty, canadian, world
2	Wet markets	china, market, wet, animal, eat, bat, wuhan, food, open, wild
3	People not following sanitary measures	people, spread, virus, follow, take, measure, distance, covid, social, travel
4	Lack of reaction/slow government response	lack, government, response, health, public, federal, slow, early, preparedness, country
5	Chinese Government slow response	china, government, world, enough, worldhealthorganization, virus, noone, act, react, early
6	No one is responsible	noone, virus, responsible, unknown, hold, everyone, think, china, blame, anyone
7	Virus, nature, animal	nature, happen, noone, mother, nobody, pandemic, answer, time, virus, prefer
8	Travel, Not closing borders	virus, human, travel, country, transmission, pandemic, animal, china, close, spread
9	World countries	china, government, country, virus, border, answer, travel, worldhealthorganization, home, close

Table 7
Summary of Survey Wave 5 topics.

Topic	Label	Top 10 Terms
1	Chinese Government, WHO	government, chinese, worldhealthorganization, trump, china, unknown, canadian, world, slow, communist
2	Wet markets	china, market, wet, animal, wuhan, open, live, eat, virus, unknown
3	People not following sanitary measures	people, follow, virus, social, take, distance, measure, health, isolate, rule
4	Travel, Not closing borders	china, government, enough, travel, border, close, worldhealthorganization, soon, slow, act
5	Lack of reaction/slow government response	virus, lack, china, government, spread, health, world, public, response, country
6	No one is responsible	noone, responsible, virus, unsure, hold, anyone, happen, nobody, unknown, particular
7	Nature, Nobody	nature, human, mother, noone, bat, world, unknown, animal, natural, eat
8	Poor government response	lack, poor, country, government, virus, china, get, unknown, bad, noone
9	Virus	china, virus, spread, worldhealthorganization, travel, world, unknown, government, nobody, time

Table 8
Summary of Survey Wave 8 topics.

Topic	Label	Top 10 Terms
1	People not following sanitary measures	people, follow, mask, rule, distance, wear, health, guideline, social, public
2	Chinese government, WHO	government, chinese, worldhealthorganization, china, canadian, federal, communist, unknown, slow, trudeau
3	No one is responsible	noone, responsible, virus, nature, happen, think, nobody, anyone, blame, particular
4	Travel, Not closing borders	china, travel, market, international, country, wet, world, virus, unknown, everyone
5	Wet markets	china, market, animal, wet, human, food, virus, eat, bat, people
6	Lack of government early measures	enough, government, soon, worldhealthorganization, unknown, china, border, take, close, early
7	Lack of reaction/slow government response	government, lack, canada, slow, action, unitedstates, response, federal, nature, country
8	Virus	virus, china, spread, world, know, unknown, start, pandemic, country, laboratory
9	People	people, go, virus, trump, government, party, canada, everyone, unknown, say

4.4.3. *Travel and not closing borders*

The prevalence of this topic fluctuates over time and gradually decreases from 14.3 % at survey wave 1 to 7.6 % at survey wave 10. This topic refers to ongoing travel and opened borders as being responsible for the COVID-19 crisis. Some participants identify travel in relation to the lack of health precautions: "*International travel without adequate health and safety precautions*" and "*Idiotic behavior from selfish individuals who travelled abroad and did not confine themselves as required*." Participants also criticize the government for not acting quickly enough, for instance by closing borders: "*Once an outbreak happened travel should have been stopped to minimize the impact. However we were warned a pandemic would happen, and governments did not listen*" and "*Not shutting down the country fast enough to international travel*."

4.4.4. *No one, responsibility ascribed to nature or climate change*

The predominance of this topic fluctuates over time, from 18.8 % at survey wave 1 to 15.9 % at survey wave 10. It includes the following subtopics: 1) no specific responsible party, 2) nature and the environment, and 3) climate change. Some participants mentioned that no one was to blame or that it was a coincidence: "*Fate - Pandemics happen occasionally and no one can be completely prepared for everything.*" and "*No one. It was a naturally occurring event that was bound to happen sooner or later.*" Others point to the environment or the climate crisis: "*Mother Nature this virus is part of our natural environment.*", "*Climate Change and Mother nature forcing us to behave properly.*"

4.4.5. *Lack of government reaction and slow response*

The prevalence of this topic increases gradually over time, from 12.9 % at survey wave 1 to 20.0 % at survey wave 10. Participants point to the lack of promptness or preparation of the Canadian government to act against the virus, or its slowness to respond to the pandemic: "*Governments' slow response to it, for example late lockdown measures, border closings, etc.*" and "*Both the federal and provincial governments' slow response to activities that were going on abroad. At the very least, back in early January, PPE*[3] *stocks and hospital/LTCH*[4] *procedures should have been reviewed.*"

4.4.6. *People who do not follow sanitary measures*

The prevalence of this topic increases between survey waves 1 and 5,

[3] Personal protective equipment.
[4] Long-term care home.

Table 9
Summary of Survey Wave 10 topics.

Topic	Label	Top 10 Terms
1	People not following sanitary measures	people, follow, guideline, rule, health, mask, distance, wear, social, public
2	Canadian government response	government, virus, federal, provincial, country, enough, measure, act, canadian, border
3	Wet markets	china, market, animal, wet, human, virus, bat, eat, chinese, wuhan
4	Chinese government, WHO	government, chinese, worldhealthorganization, trump, china, federal, trudeau, unsure, American
5	Lack of reaction/slow government response	virus, china, lack, spread, action, slow, control, start, early, begin
6	No one is responsible	noone, responsible, hold, anti, blame, virus, anyone, masker, unknown, crisis
7	Travel, Not closing borders	take, travel, world, seriously, people, everyone, pandemic, virus, enough, population
8	Nature	nature, mother, politician, unknown, response, society, crisis, everyone, think, health
9	Unknown	get, need, us, covid, unknown, like, people, party, political, trudeau

and more rapidly between waves 8 and 10 to become largely dominant. The proportion of responses increases from 11.4 % at wave 1 to 27.9 % at wave 10. Examples include: “*People who don't follow health guidelines for example: anti-maskers and covid-19 deniers.*” and “*People not wearing masks, not social distancing and not respecting bubbles. There is no need to shop as a form of entertainment.*

4.5. Canadian-specific blame dynamics

While the topics generated by LDA did not unveil specific elements of Canadian blame, a closer examination of the top 10 terms characterizing each topic reveals a few terms indicative of the Canadian context (see Tables 5–9). At survey waves 1, 3, and 5, there are no words explicitly referring to the Canadian context, except for the occasional appearance of the term “Canada”, “Canadian” or “federal” in a few topics. However, at survey waves 8 and 10, the word “Trudeau” emerged in some topics, such as “*Chinese Government, WHO*” and “*Travel, Not closing borders*”. This refers to Canada's Prime Minister during the COVID-19 crisis, Justin Trudeau. Further exploration of potential hypotheses explaining the limited Canadian context in blame will be addressed in the discussion.

5. Discussion

5.1. Blame phenomenon during COVID-19

The COVID-19 crisis can be understood as a dramatic social change (DSC), (de la Sablonnière et al., 2013; de la Sablonnière, 2017; de la Sablonnière et al., 2020; Caron-Diotte et al., 2022). This crisis has led to sudden, profound, and impactful social transformations amongst populations around the world. It has also led to feelings of confusion and ambiguity among individuals who have no control over the situation. The lack of clarity and control over the situation thus leads people to seek for responsible parties. Public perceptions of who is responsible for the origin and spread of COVID-19 are influenced by factors such as the geographic proximity of the epidemic and the actions of individuals (Mayor et al., 2012; Roy et al., 2020). Specifically, blame and scapegoating tend to fluctuate depending on the state of the epidemic; when the disease is considered remote, blame focus on distant communities, and when the disease is considered close, blame shifts to local communities (Mayor et al., 2012; Roy et al., 2020). In the present study, we analyzed the changing dynamics of blame attribution and scapegoating during the COVID-19 crisis among a representative sample of the Canadian population through a longitudinal survey by using LDA, an automatic text analysis method. Our results show that blame is primarily focused on distant communities (Chinese government and WHO) and then shifts to local communities (people who do not follow sanitary measures). Six topics are recurrent in each survey wave: 1) Chinese Government and World Health Organization; 2) Wet markets; 3) Travel and not closing borders; 4) No one, responsibility ascribed to nature or climate change; 5) Lack of government reaction and slow response; 6) People who do not follow sanitary measures. These topics will be discussed in more detail in the following paragraphs.

5.1.1. Chinese Government and World Health Organization (WHO)

These two themes, namely the Chinese Government and WHO, were both generated under one topic by LDA, due to their frequent co-occurrence in participants' answers. This association also stems from their roles as among the first actors in the COVID-19 crisis. Notably, WHO declared COVID-19 a pandemic and the first cases of the virus were detected in the city of Wuhan (de Rosa & Mannarini, 2020). Furthermore, China was accused of not advising WHO sooner about the pandemic.

Previous research demonstrate that WHO is perceived as the main actor responsible for fighting worldwide disease (Mayor et al., 2012). Given its prominent role in the initial detection and response of the virus, this organization faced criticism for allegedly censoring information and for not responding quickly enough (Choli, & Kuss, 2021). According to Wagner-Egger et al. (2011), some people consider the actions of international organizations, such as WHO, to be useful, while others express distrust. This blaming tendency may come from high expectations for timely actions during a rapidly evolving public health crisis. In our study, WHO was also singled out for its perceived failure to effectively contain the virus at its point of origin. At the early stages of the pandemic, WHO was possibly one of the most readily available scapegoat for COVID-19, along with China.

In the early stages of the outbreak, the Chinese government's response became a focal point of global attention. Consistent with our findings, previous studies indicate that the Chinese government was accused of concealing or censoring information about the COVID-19 pandemic (Choli, & Kuss, 2021; Nguyen et al., 2021). Information restriction by the Chinese government led to the population's ignorance and lack of preparedness for the COVID-19 pandemic as well as distrust (Shangguan et al., 2020). Assigning blame to the Chinese government may have acted as a coping mechanism for people seeking a tangible explanation at a time when not much was known about the COVID-19 virus. Through this process, people found a way to channel their negative emotions toward a specific entity, especially as national governments started to implement unprecedented health and economic measures such as the closure of non-essential businesses and restrictions on gatherings, heightening the societal stress and anxiety levels.

Moreover, participants in our study indirectly singled out Asian communities as responsible for the COVID-19 crisis by blaming specific places associated with cultural practices, such as wet markets (see next paragraph). This perception is rooted in an essentialist view of Asian culture, reducing it to stereotypical aspects, which can contribute to the stigmatization of Asian communities and reinforce prejudices (Hardy et al., 2021). Our results are somewhat different from the findings of Ferrante et al. (2022), which suggest that the majority of Canadians have low levels of prejudice towards Asians throughout the pandemic. As our study employed an open-ended question format, participants had the opportunity to express their thoughts, revealing nuanced opinions (Joffe, 1999), including indirect expressions of prejudicial attitudes (Desmarais et al., 2023). Although prejudice tends to be resistant to change, its intensity may increase during crisis situations (Allport, 1979). Previous studies have concluded that there was an increase in prejudice towards Asians during the COVID-19 crisis (Choli, & Kuss, 2021; de Rosa & Mannarini, 2020; Dionne & Turkmen, 2020; Hardy et al., 2021; Ittefaq et al., 2022). Furthermore, findings from Nguyen et al. (2021) demonstrate that when Asians are blamed for COVID-19, they are mostly singled out for the occurrence of the disease rather than its transmission. This suggests that they may be blamed for the origin of the pandemic rather than its spread.

5.1.2. Wet markets

Wet markets are places where food intended for consumption is sold. Historically, the consumption of wild animals sold in wet markets has been a practice viewed as "unhealthy" and "primitive" by many Westerners (Desmarais et al., 2023; Labbé et al., 2022; Nguyen et al., 2021). Participants in our study often refer to the animals sold in these markets and its unsanitary or unhealthy aspects, which may be linked to disease outbreaks. Consequently, "hotter" emotions, such as disgust, are directed towards already derogated and stigmatized groups (Joffe, 2011).

Blaming wet markets is not solely based on scientific evidence but is also influenced by cultural biases and preconceived notions (Monson, 2017). With Wuhan considered the origin of the pandemic, discussions on the market's sanitary conditions exemplify how scientific discourse can be used to depict a community as dangerous (Desmarais et al., 2023). This perception of unhealthiness and primitiveness also extends to specific communities during health crises. For instance, during the H1N1 influenza pandemic from 2009 to 2010, impoverished communities in Mexico were held accountable for the emergence of the virus, primarily due to their purportedly unhygienic habits (Wagner-Egger et al., 2011). Indeed, the discrimination of racialized "Others" is often subtly expressed through "borderline racism", or 'impartial' discourses that criticize their behaviors, beliefs, knowledge, information, and rationality as a means to affirm their inferiority (Desmarais et al., 2023).

There are different varieties of wet markets that do not necessarily involve the sale of exotic or live animals (Lin et al., 2021). Indeed, wet markets and live-animal or exotic markets are often confused with one another (Lin et al., 2021), a phenomenon that was observed in our study. In other studies, Asian culinary traditions have also been blamed as the cause of the pandemic (Barreneche, 2020; Desmarais et al., 2023), leading some of the population to avoid Chinese and Asian restaurants in particular (Labbé et al., 2022). Misconceptions about wet markets and Asian food culture can amplify xenophobic attitudes towards these communities (Lin et al., 2021).

5.1.3. Travel and not closing borders

These two themes (travel and not closing borders) were both generated under one topic by LDA. This may be due to the fact that participants often mention both travel and not closing borders in their responses. They often refer to individual behavior when referring to travel and often refer to government decisions when it comes to non-closure of borders. This topic therefore encompasses both individual and institutional blame.

One of the reasons travel is blamed is its potential to bring the virus into the country. In a study by Nguyen et al. (2021), participants identified tourism and international travel as the primary reason for the spread of COVID-19. Travelers were also portrayed as responsible for spreading the COVID-19 virus through Canadian editorial cartoons, with blame attributed to both individuals returning to Canada and those who violated travel restrictions (Labbé et al., 2022). Some criticized travelers for not showing solidarity with the rest of the population, which had to cope with health restrictions (Labbé et al., 2022).

During the COVID-19 pandemic, many individuals called on their respective governments to close borders, particularly Chinese borders (Choli, & Kuss, 2021). Borders have a significant historical role in managing a pandemic, as they represent a geopolitical and symbolic barrier between sick and healthy individuals (Abeysinghe, 2016). Vulnerability to disease gives rise to exclusionary immigration attitudes, since foreigners are often perceived as carriers of illnesses (Green et al., 2010). Closing borders would then create a sort of "protective barrier" for individuals with irrational fears of strangers and sick people (Abeysinghe, 2016). From this perspective, the nation represents an idealized and reassuring space of protection against threatening epidemics. Governments that do not push for border control or confinement of the nation are seen as incompetent and at fault (Abeysinghe, 2016).

In our study, we observed a shift in the perception of blame towards travel and border control as the pandemic progressed. At the start of the pandemic, when the virus was widely perceived as originating from abroad, travelers and the perceived failure to close borders were particularly blamed. This could be due to a direct association between international travel and the introduction of the virus into the country, as mentioned at the beginning of this section (Monson, 2017). However, as the virus began to spread locally and community cases increased, the focus on international travel as the main source of transmission diminished. People may have realized that the virus also circulated within national borders, independently of international travel. In addition, the subsequent actions taken by the Canadian government regarding border control may have influenced public perception and diminished criticism concerning the decision not to close borders earlier.

5.1.4. No one, responsibility ascribed to nature or climate change

Some participants did not attribute responsibility for the COVID-19 crisis to any human factor or attributed it to the climate change crisis. They identified either 1) no specific culprit, or 2) nature and the environment, and 3) climate change. Notably, if people are aware that blaming diseases on specific groups has caused harm in the past, it might affect how they see the current pandemic and who they hold responsible for it (Joffe, 2011). Furthermore, some participants may adhere to scientific arguments suggesting that the COVID-19 pandemic may be a consequence of climate change (Mora et al., 2022).

This topic is also evident in other population-based surveys about blame attribution during COVID-19, such as Nguyen et al. (2021), Hardy et al. (2021), and Rateau et al. (2021). However, it did not emerge in other types of studies, such as social network analyses (Choli, & Kuss, 2021) and media and institutional discourse analyses (de Rosa & Mannarini, 2020; Ittefaq et al., 2022; Labbé et al., 2022). Yet these are frequent themes in the attribution of responsibility during COVID-19. Specifically, either the public does not attribute responsibility for the COVID-19 crisis to any human factor, or believe that the origin of the virus is non-human and unintentional (Nguyen et al., 2021; Rateau et al., 2021). According to findings from Hardy et al. (2021), these tendencies vary across the political spectrum: individuals identifying as left-wing or apolitical were more likely to claim that there is no one responsible for the COVID-19 crisis than others.

5.1.5. Lack of government reaction and slow response

Blame attribution in the present research evolved as the pandemic spread locally, centering on the perceived lack of reaction and slow response of governments. Authorities were blamed for their lack of action, haphazard approach to the pandemic, and perceived ineffectiveness in combating the virus as it spread, leading to a deterioration in the situation (de Rosa & Mannarini, 2020; Douglas, 1992; Joffe, 2011). Attribution of blame to governments at later stages of the pandemic suggests that they are now perceived as key actors holding the responsibility to act in the face of the crisis, similar to the way WHO was initially perceived as a pivotal actor at the beginning of the outbreak. Indeed, governments and public health authorities were responsible of both implementing and withdrawing sanitary measures when the virus entered the country.

These "upward" blaming tendencies may suggest the presence of a dynamic of distrust towards governments, whose actions are perceived as harmful to the population (Hardy et al., 2021; Joffe, 2011; Mayor et al., 2012; Monson, 2017). The growing distrust of the authorities, and the politicization of previous epidemics could explain this phenomenon (Choli, & Kuss, 2021). Individuals may also feel a heightened sense of control when naming governments as responsible for the crisis, as they have the ability to hold them accountable (Choli, & Kuss, 2021). While it is possible that adequate preparation and effective response by governments can reduce blame attribution and scapegoating for sudden and unexpected events, a new blame rhetoric is always likely to emerge due to the inherent uncertainty of such events (Nguyen et al., 2021). Attribution of blame can shift people's attention away from governmental and collective efforts to manage the crisis, making these efforts appear less effective (Nguyen et al., 2021).

5.1.6. People who do not follow sanitary measures

The results of the present study are consistent with previous research indicating that individuals who do not comply with sanitary measures such as social distancing, wearing masks, and restrictions on public gatherings, are predominantly identified as responsible for the crisis during later phases of the COVID-19 pandemic (Labbé et al., 2022; Nguyen et al., 2021). The shift in blame attribution towards people not following guidelines can be linked to the changing dynamics of the pandemic. In the initial stages, when community transmission was low, blame may not have been as pronounced. However, as time progressed and community transmission cases increased, blaming tendencies intensified. As the understanding of the virus and the importance of individual behavior in controlling its spread became more prominent, blame shifted towards those not following recommended guidelines. Participants who adhered to the sanitary measures may have directed blame towards those who did not, as the virus persisted despite collective efforts to prevent its spread. In our study, these blaming tendencies particularly emerged when local Canadian governments imposed restrictions on social gatherings during the holiday season, citing the contagious nature of the virus (Aubin, 2020).

Libeling is a typical strategy of blame, scapegoating and rejection (Douglas, 1992). Our findings indicate that the term "irresponsible" is used by some participants to describe those who do not follow guidelines. Non-compliant individuals were depicted as "immoral", "stupid" and "self-centered" in Canadian editorial cartoons (Labbé et al., 2022). The neologism "covidiot", a combination of "covid" and "idiot", has also been used to describe individuals who do not follow health measures (Labbé et al., 2022). During times of crisis, military language involving a narrative construction of "heroes", "villains", and "victims" has often been used in the public space. The COVID-19 pandemic is no exception. Non-compliant individuals have been singled out as villains, since they were perceived as not willing to do their part for the common good (Barreneche, 2020).

Moreover, in contemporary Western society, maintaining health is a fundamental value, perhaps even a metaphor for virtuous conduct (Brandt & Rozin, 1997). In this context, blaming individuals for not following sanitary measures can reveal an ethic of self-discipline and self-regulation, and a strategy to encourage them to comply with the rules (Douglas, 1992; Labbé et al., 2022; Petersen & Lupton, 2000). This attitude can lead to intolerance, exclusion or persecution of individuals who are unwilling to engage in activities as being beneficial to health, since they are perceived as being responsible for their condition (Douglas, 1992; Labbé et al., 2022; Petersen & Lupton, 2000).

5.1.6.1. Canadian-specific blame dynamics. The lack of Canadian contextual elements in blame dynamics within our study could be attributed to the federal structure of healthcare in Canada, where responsibilities are mostly administered by the provinces and territories (Government of Canada, 2019). This decentralized structure may complicate pinpointing a specific entity responsible for the blame. Additionally, varied provincial approaches to managing the pandemic could influence blame attribution. Examining blame dynamics on a provincial level may reveal more localized trends, highlighting how differences in pandemic management by each province influence public perceptions.

5.2. Change in blame attribution over time

Our results lend empirical support to the idea that attribution of blame occurs differently as the pandemic unfolds. While the Chinese government, WHO, and wet markets were singled out as the pandemic begun (i.e., the first COVID-19 wave[5]), lack of government action and slow response and individuals who do not comply with sanitary measures were blamed more as the pandemic progressed (i.e., the second wave of the virus[6]). Before survey wave 8 (between August and September 2020), sanitary measures implemented to address COVID-19 primarily focused on confinement and social distancing. Starting from survey wave 8, additional health measures were introduced, such as mandatory mask-wearing and vaccination passports. During survey wave 10 (between November and December 2020), Canadian provincial governments heavily restricted social gatherings during the holiday season, causing disappointment and sadness among the population (Aubin, 2020). This period of restrictions likely contributed to reinforcing blame attribution towards individuals who did not comply with the health measures, as they were seen as potentially responsible for the persistence of the pandemic and the risk of new waves of infections.

Furthermore, our analysis suggests that the patterns of blame attribution reflect the CSC model (Gilles et al., 2011). During survey wave 3, there was a surge in blaming distant entities such as WHO and the Chinese government, a phenomenon that aligns with the awareness stage. Indeed, representations of past diseases have demonstrated a recurrent pattern where entities like the WHO and the Chinese government are initially singled out. In this phase, the tendency towards "Othering" is particularly highlighted, where cultural practices such as wet markets are mostly targeted as responsible for the COVID-19 crisis. Survey waves 5 and 8 may be indicative of the divergence stage, as we observed a more intricate pattern of blame attribution. Finally, in survey wave 10, blame converges on individuals who do not follow sanitary measures, which may represent a notable shift towards the convergence and normalization steps.

This confirms the hypothesis that blame is initially focused on distant parties (survey waves 1, 3, and 5), and then shifts to local parties (survey waves 8 and 10). Indeed, blame attribution evolves with the proximity of the threat and the risk of international spread (Choli, & Kuss, 2021; Labbé et al., 2022; Roy et al., 2020). Blame also shifts during key periods of the pandemic, especially when the government introduces new sanitary measures. Individuals who do not adhere to these measures may be singled out by the rest of the population and face social scrutiny.

Our findings contrast with observed historical patterns of blame, scapegoating and exclusion, which show that it is primarily directed at the elites, then at disadvantaged groups, followed by outsiders (Douglas, 1992; Pegg, 1990). The differences in blame evolution can be attributed to several factors related to the specific nature of each crisis, the actors involved, the characteristics of the perceived threat, and the responses provided by authorities. In their studies on accusations of witchcraft and epidemics of leprosy, Pegg (1990) and Douglas (1992) found that these threats are rooted in the community's cultural and social beliefs, with accusations often linked to social hierarchy, social cohesion and rivalries. In contrast, blame attribution during the COVID-19 pandemic shifted based on the geographic location of the virus and government responses to public health measures.

6. Limitations

There are several limitations to this research. Firstly, identification of responsible parties for the COVID-19 crisis was measured by an open-ended question, which are often characterized by a lower response

[5] First wave of COVID-19 started in February 2020 and ended in July 2020.

[6] Second wave of COVID-19 started in August 2020 and ended in March 2021.

rate than closed-ended questions. Non-response can be explained both by a lack of interest in the question and ineloquence (Roberts et al., 2014). Some of the answers given by participants can be vague and difficult to interpret. Short and vague answers do not provide enough information to be included in the topics generated by LDA (Crain et al., 2012; Pietsch & Lessmann, 2018) because the model relies on the simultaneous presence of two or more words to obtain meaningful topics (DiMaggio et al., 2013; Nelson, 2020).

Secondly, the phrasing of the open-ended question made no distinction between the origin and spread of COVID-19. Asking participants two questions, one about the origin of the virus and the other about the spread of the virus, would provide a more detailed analysis of blame attribution during COVID-19. Based on our survey results, we believe that participants refer to the origin of the virus during the early phases of the pandemic, whereas they refer to the spread of the virus during the later phases of the pandemic.

Finally, LDA also has some limitations, referring particularly to the choices that must be made before the analysis is performed (Nelson, 2020). Researchers must make several decisions regarding the pre-processing steps, all of which can produce different results (Nelson, 2020). Furthermore, because the analysis is data-driven, researchers do not know the number of topics that should be extracted before the analysis (Nelson, 2020). There are several methods that can be used to determine the appropriate number of topics to analyze, and these are the subject of debate among researchers (Nelson, 2020). Finally, themes with very few responses are unlikely to appear in topics (Roberts et al., 2014) unlike manual coding, where all answers, even the rarest ones, are categorized. For example, some participants blamed Asians for the COVID-19 crisis. However, as only few respondents are concerned, no topic related to this phenomenon emerged.

7. Conclusion

The goal of this paper is to track the changing dynamics of blame attribution and scapegoating in the Canadian population as the COVID-19 pandemic unfolds, focusing on the influence of evolving public health measures. It provides empirical evidence of the shifting patterns of blame from distant to local collectives as the COVID-19 pandemic unfolds. This research highlights the role of geographic proximity and perceived risk in shaping public perceptions of the pandemic. It also shows that blame shifts depending on key periods during the pandemic, notably the implementation of new sanitary measures by the government.

These findings have implications for future public health crises as they emphasize the important role of targeted communication strategies in promoting responsible behavior. Indeed, the inherent uncertainty of health crises can contribute to blame-seeking and scapegoating in the public, confirming the need for authorities to adopt a comprehensive and well-coordinated approach to mitigate these tendencies. Understanding the shifting patterns of blame attribution highlighted in our study enables authorities to anticipate potential blame dynamics during different phases of a crisis. Moreover, recurring patterns of blame and scapegoating during challenging events suggest the existence of underlying psychological and social processes that go beyond the particular features of each individual crisis. The ongoing phenomenon of blame attribution and scapegoating in times of crisis bears witness to a common human tendency to seek explanations, assign responsibility and cope with uncertainty.

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CRediT authorship contribution statement

Marianne Chevalier: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Roxane de la Sablonnière:** Writing – review & editing, Visualization, Validation, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Simon-Olivier Harel:** Writing – review & editing, Software, Resources, Methodology. **Sylvie Ratté:** Writing – review & editing, Software, Resources, Methodology, Investigation. **Mathieu Pelletier-Dumas:** Writing – review & editing, Project administration, Data curation. **Anna Dorfman:** Writing – review & editing, Project administration, Data curation. **Dietlind Stolle:** Writing – review & editing, Project administration. **Jean-Marc Lina:** Writing – review & editing, Project administration. **Éric Lacourse:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssaho.2024.100825.

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