Using sentiment analysis of Twitter discourse to understand sentiment towards salmon aquaculture among stakeholders over time

by
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ABSTRACT

The intersection of the environment, the economy and society create a wicked problem in salmon aquaculture in Canada. To provide a unique insight into the challenges of the salmon aquaculture industry amongst key stakeholders, this thesis investigates the sentiment of several important stakeholder groups in the salmon aquaculture industry: academics, industry, ENGOs, Government, Indigenous peoples, and the media. By scraping data from Twitter from the years 2006 to 2021, it examines aquaculture sentiment from a global English-speaking view, as well as a subset of Canadian data. This thesis addresses the following questions: How does public sentiment towards salmon aquaculture differ over time? How does public sentiment towards salmon aquaculture differ among stakeholder groups?

Data is analyzed through a stakeholder management theory framework using sentiment analysis. Data is collected from Twitter because users prefer it to other social media sites to share their unprompted thoughts, ideas, and opinions. The data is scrapable using the open-source Twitter scraper Twint. The data is processed using Google Colab notebooks: raw data is preprocessed into 273,319 tweets (rows) of clean data, which are analyzed using VADER's natural language processing tool, yielding a sentiment score between -1 and +1 for each tweet.

This thesis explores the dependent variable of sentiment and the independent variable of time. Findings are examined through the lens of overall sentiment, sentiment from year to year (2006-2021), sentiment per stakeholder category, and sentiment per stakeholder category per year. Sentiment from 2007 to 2021 is expected to be increasingly negative because of significant negative events in the salmon aquaculture industry from 2006 to 2021. There have been many policy changes, lawsuits, fish escapes and concerns from ENGOs, Indigenous groups, and researchers about salmon aquaculture during this time. However, the data contradicts this hypothesis by trending positively over time.

The overall dataset is consistent and clusters around a mean of 0.3 (slightly positive), a median of 0.4 and a standard deviation of 0.4. The skewness of the general data is -0.994, meaning that the distribution has a moderate negative skew (most tweets have positive sentiment). The dataset has an R-squared value of 0.64, meaning that the data represents a moderate model, and an R-squared value of 0.79 (when removing outliers) shows an absolute strong model. All eight stakeholder group categories display a moderately negative skewness value and a positive mean sentiment. The Academic / Researcher Group and the Industry / Worker stakeholder groups show strong models, and the other stakeholder categories with lower R-squared values show weaker models.

This thesis provides new insight into the growing and expanding salmon aquaculture industry. Further, understanding stakeholder sentiment can allow a government, individual, or group to be more proactive in its decision-making rather than reactive. The data allows for open dialogue with all stakeholders and promotes future research, analysis, and collaboration within the salmon aquaculture industry.

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INDIGENOUS AFFIRMATION

We pay respect to the Algonquin people, who are the traditional guardians of this land. We acknowledge their long-standing relationship with this territory, which remains unceded

Ni manàdjiyànànig Màmìwininì Anishinàbeg, ogog kà nàgadawàbandadjig iyo akì eko weshkad. Ako nongom ega wìkàd kì mìgiwewàdj.

We pay respect to all Indigenous people in this region, from all nations across Canada, who call Ottawa home.

Ni manàdjiyànànig kakina Anishinàbeg ondaje kaye ogog kakina eniyagizidjig enigokamigàg Kanadàng eji ondàpinangig endàwàdjin Odàwàng.

We acknowledge the traditional knowledge keepers, both young and old.

Ninisidawinawànànig kenawendamòdjig kije kikenindamàwin; weshkinìgidjig kaye kejeyàdizidjig.

And we honour their courageous leaders: past, present, and future.

Nigijeweninmànànig ogog kà nìgànì sòngideyedjig; weshkad, nongom; kaye àyànikàdj.

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List of Acronyms

API	Application Programming Interface
B.C.	British Columbia
BCAFC	British Columbia Aboriginal Fisheries Commission
CAAR	Coastal Alliance for Aquaculture Reform
CAIA	Canadian Aquaculture Industry Alliance
CEPA	Canadian Environmental Protection Act
CSV	Comma Separated Value
DFO	Department of Fisheries and Oceans
ENGO	Environmental Non-Governmental Organization
FAO	Food and Agriculture Organization of the United Nations
IK	Indigenous Knowledge
JSON	JavaScript Object Notation
MAACFA	Minister of Agriculture's Advisory Council on Finfish Aquaculture
NLP	Natural Language Processing
OSINT	Open-Source Intelligence Tool
PRV	Piscine orthoreovirus
RT	Retweet
SAR	Salmon Aquaculture Review
SI	Sustainability Indicator
TEK	Traditional Ecological Knowledge
UBC	University of British Columbia
U.S. EPA	The United States Environmental Protection Agency
VADER	Valence Aware Dictionary and sEntiment Reasoner

INTRODUCTION

There is no international legislative body or international treaties which govern the global salmon farming industry. Even within Canada, different governing bodies regulate salmon aquaculture and farming practices. Some stakeholders see the federal Ministry of Fisheries and Oceans (colloquially known as DFO) as an organization with the conflict of a dual mandate to protect wild salmon stocks while also promoting the salmon aquaculture industry (Yurtoğlu, 2018). DFO is a federal ministry, but its responsibility concerning regulating salmon aquaculture is not uniform across Canada (Flaherty et al., 2019).

Salmon aquaculture is a lucrative business on Canada's Atlantic and Pacific coasts. However, many continue to oppose the industry due to conflicting scientific studies about potentially adverse wide-scale effects on the wildlife and environment (Flaherty et al., 2019). Wild salmon (a keystone species) help support the biodiversity of the surrounding area and viruses and pollution from fish farms can significantly affect the balance of the natural environment (Huff, 2019). The aquatic environment comprises marine and freshwater ecosystems, covering roughly 72% of Earth's surface (Jarić, 2020). Aquatic species are more at risk than their fellow terrestrial species and face higher extinction rates, impacting the well-being of those communities that depend on them (Jarić, 2020).

Fewer conservation and research resources are allocated to aquatic ecosystems than to terrestrial ones: this paper seeks to add to our understanding of aquatic ecosystems. Culturomics and iEcology are emerging fields of research that mine digital data. They are far less costly than fieldwork and social surveys. IEcology focuses on studying digital data using automatic tools to discover patterns in the natural world for understanding human-nature interactions better (Correia et al., 2021; Jarić, 2020). In iEcology, views and opinions are in context and are spontaneous and public, rather than researcher-prompted, which may offer better and unbiased data. Several studies show a negative connotation in news media or local surveys (Froehlich et al., 2017).

The conceptual framework for this thesis is stakeholder theory, and the primary method is software-assisted sentiment analysis. Edward Freeman explains the stakeholder theory in 1984 (Freeman et al., 2018, pg. 2). The stakeholder perspective is a different way of understanding the link between how companies and people create value and trade with one another (Freeman et al., 2018, pg. 1). Stakeholder theory asks for whom we create value (Freudenreich et al., 2019). The stakeholder concept is simple yet misleading. It can be easy to identify those stakeholders who are affecting the firm, or those stakeholders whom the firm affects. However, managing relationships with them can be difficult (Freeman et al., 2018, pg. 246). The theory holds that company leaders must understand their stakeholders and their needs and meet them. Stakeholder theory holds that it is unethical and unjust to only prioritize increasing shareholder wealth and that the corporation is part of a larger social community and not a separate entity.

Sentiment analysis is a method within the realm of natural language processing (Hutto & Gilbert, 2014). It is a software-assisted process that researchers can use on text (like tweets) to extract people's feelings, opinions, and thoughts (Ferreira et al., 2019; Öztürk & Ayvaz, 2018). Many systems and programs are helpful for this data analysis and the specific needs of the research rely on them. For example, the Valence Aware Dictionary and sEntiment Reasoner, or VADER, is a sentiment analysis tool available for use in Python's software that determines the sentiment scores of short and specific texts, like tweets (Singh, 2021). Researchers can process a text using VADER and give it a 'score' in the range of -1 to +1. This score is a compound score of the positive, negative, and neutral scores, which is then normalized between -1 and +1 (Singh, 2021). If the compound score is closer to +1, the text is more positive and less negative; if the score is closer to -1, the text is more negative and less positive (Singh, 2021).

With the right Open-Source Intelligence Tools (OSINT) and expertise, digital data represent a rich and unique resource for marine conservation research (Jarić, 2020). This thesis uses OSINT tools like Twint, a Twitter web scraper, and VADER, to process and analyze tweets researchers collected from Twitter. Twitter data offers an essential source of pragmatic, unfiltered public opinion about public debate or concern (Flaherty et al., 2019). See the Methods section below for a discussion of data collection and analysis techniques.

Twint and VADER make it possible to collect and process thousands of global tweets from 2006 to 2021. It allows for an in-depth look at sentiment about salmon aquaculture from various stakeholders in a consistent and relatively unbiased manner. The thesis looks at international tweets but only focuses on those in English. This method is helpful to explore the dependent variable of sentiment and the independent variable of time. The thesis looks at stakeholder groups' sentiments toward salmon aquaculture over time and provides a broader picture of sentiment. This thesis also explores sentiment trends on the more positive or negative side and determines if there are any significant upward or downward trends around big ‘events’ in the salmon aquaculture industry, such as policy change, moratoriums, protests, or other events. Finally, the data can be compared from a global English-speaking perspective to a solely Canadian perspective to see if there are any differences or similar patterns.

Understanding the sentiment of different stakeholder groups in the salmon aquaculture industry is vital to understanding the *what* and the *why* of the opinions and views of various stakeholders. Overall, the hope for the industry is that opinion about salmon aquaculture becomes more positive over time. Hopefully, a more positive outlook would indicate better policies, more sustainability and efficiency, and a lack of issues like pollution or fish escapes. On the other hand, a more pessimistic view would suggest that activist critiques of salmon aquaculture are entrenching in public discourse, leading to intensification rather than moderation of controversy.

Initially, I pulled 536,988 English-language tweets from Twitter. I removed tweets if they were retweets, did not have a user, were not in English, did not contain the word 'aquaculture', or did not have a user bio. Once I could process the tweets and analyze them through VADER, the dataset had 273,319 remaining individual, unique tweets. Within the Canada subset, there are 3,377 tweets (1.23% of the overall dataset). In addition, to create graphs and process the findings one step further, a removal process was necessary to remove any tweets with a neutral score to compare positive and negative compound sentiment scores. Neutral is not the best word to describe these tweets, as they are not neutral due to a lack of either positive or negative sentiment. Rather, they are tweets that may use the word ‘aquaculture’ in passing or are tweets that are meant to be informative. These tweets typically do not express an opinion: they spread or share information. An example of this is “I attended an Aquaculture Conference in Canada this weekend”. The keyword is mentioned; however, it is done in passing and would receive a neutral score from VADER as it does not lean positively or negatively. Neutral scores are removed to better examine the positive and negative sentiment of the tweets, as neutral tweets are not of importance to examine in answering the thesis question. Results are explorable through the lens of overall sentiment, sentiment from year to year (2006-2021), sentiment by stakeholder category, and sentiment by stakeholder category per year.

From the global perspective, the positive may outweigh the negative: a lot of the English-speaking countries have had positive experiences with the aquaculture industry. Looking at the negative lean of Canadian events from 2007 to 2021 in Appendix A, one would expect Canadian sentiment to be more negative than positive since significant events in the salmon aquaculture industry from 2006 to 2021 did not seem optimistic. In Canada, there have been many policy changes, lawsuits, fish escapes and concerns from ENGOs, Indigenous groups and researchers about salmon aquaculture; however, the data seems to trend positively over time for most stakeholders. The overall dataset is consistent with a moderate negative skew of data (most tweets are positive).

RESEARCH QUESTIONS

In this thesis, I analyze trends in stakeholders' sentiment over time. The dependent variable in this thesis is sentiment and the independent variable is time. I investigate if sentiment tends to be more positive or negative overall or whether it changes between specific stakeholder groupings and then determine if there are any temporal trends or major trends surrounding significant 'events' in the salmon aquaculture world. The thesis looks at global tweets available on Twitter, however, these are only English-language tweets that are being analyzed.

This analysis is helpful to all stakeholder groups. In industry, firms can see how different groups perceive salmon aquaculture and determine which groups have the most impact on their business. Conservationists and ENGO groups can use data and the sentiment analysis method to determine the critical areas of interest and know which topics to push on and which lack attention. For researchers, the analysis highlights the significant gaps in missing data or avenues due to a lack of current information.

Knowing the sentiment analysis of salmon aquaculture allows these different stakeholder groups to react accordingly and allows for better collaboration between them. Analyzing the temporal scales of changes in sentiment can also develop a better understanding of the industry as a whole and what direction it may be heading in as it tries to build and grow. Therefore, the research questions guiding this analysis are:

1. How does public sentiment towards salmon aquaculture differ over time?
    a. Does sentiment trend more positively or more negatively over the period? Does it fluctuate over time?
    b. Are spikes in attention and sentiment connected to specific events?

2. How does public sentiment towards salmon aquaculture differ among stakeholder groups?
    a. Is the sentiment typically more positive or more negative, and for whom? Does sentiment fluctuate within and across groups over time?

THE CASE

Salmon Aquaculture in Canada

Canada's 202,080 km coastline is largely undeveloped and has enormous potential for several types of aquaculture (Flaherty et al., 2019). Canada's stretch of coast accounts for approximately 25% of the world's coastline (Flaherty et al., 2019). Aquaculture is a catchall term for farming aquatic species and plants for harvest. Small-scale stocking ponds are the first types of aquaculture production, and now there is industrial-scale production within the last few decades (Young et al., 2019). Aquaculture in Canada is diverse, and production splits into two primary industries of marine and freshwater species. There are shellfish and finfish sectors within both industries and they both use different techniques to produce different marine species (Rayner & Howlett, 2007). Salmon aquaculture accounts for 65% of Canada's aquaculture production (by volume) and 70% (by value), as Canada is the fourth-largest producer of farmed salmon (Flaherty et al., 2019; Young et al., 2019). Despite this, Canada only controls 0.2% of the global market share for aquaculture (Flaherty et al., 2019).

Issues & Controversy in Canadian Salmon Aquaculture

There are many issues within the new salmon aquaculture industry in Canada and many experts see governance of the industry as a "wicked problem" (Flaherty et al., 2019). For salmon aquaculture governance to improve across Canada, the challenges, experiences, and decisions need analysis and comparison with all regions of the country (Young et al., 2019). In Canada, DFO leads the management of the coastline and most marine resources in Canada (Silver, 2014). This management includes allocating commercial fisheries licenses and regulating the conditions under which First Nations conduct ceremonial and food harvests (Silver, 2014). DFO predicts an increase in demand for finfish such as salmon for consumption in the upcoming decade due to population and income growth, urbanization, and dietary changes (Flaherty et al., 2019; Hishamunda & Ridler, 2003). This problem poses a fundamental challenge for salmon aquaculture regulation and maintenance for sustainable and efficient growth. The regulation aims to create an orderly and sustainable environment for salmon aquaculture development (Hishamunda & Ridler, 2003). Canada's federal and provincial governments support the development of salmon aquaculture and have since the 1980s as it is an essential tool for rural development; however, Canadian federalism complicates governance and regulation (Young et al., 2019). In 2002, DFO includes "sustainable development" as a part of their policy objective(s) in 'DFO's *Aquaculture Policy Framework*' (Milewski & Smith, 2019). The idea is that having such rules and regulations would reduce negative externalities like pollution and conflict over water and land rights due to an open-access property regimes (Hishamunda & Ridler, 2003). As an agri-food business, the salmon aquaculture industry is deeply affected by changes in consumer sentiment, especially with regard to alternatives to aquaculture salmon (Young & Liston, 2010).

Since its inception in Canada, there has been a high degree of controversy within the salmon aquaculture industry, especially regarding the environmental concern and the lack of inclusion of First Nations groups in policy-making. On the West Coast of Canada, many ENGOs are operating public campaigns against the salmon farming industry, especially the same industry on the Atlantic coast (Flaherty et al., 2019). There is much deliberation as to whether oceans are common property for Canadian citizens, making policy and governance something that needs further exploration (Silver, 2014). In Canada, the modern form of salmon aquaculture policy did not emerge until 1984, when the federal government did a complex multi-level process of policy renewal after almost a century of benign neglect (Rayner & Howlett, 2007). As a result, the government has a lack of innovation and an inability to coordinate federal and provincial initiatives (Rayner & Howlett, 2007).

The main controversy surrounding aquaculture can be grouped into one of four main categories: environment, human health, rights, and development (Young & Liston, 2010). A lot of the opposition to aquaculture in Canada comes from two major sources: organized groups who object due to environmentalist reasons, and local stakeholders with a wider variety of complaints grounded in “historical realities and grievances of Aboriginal and non-Aboriginal coastal people” (Young & Liston, 2010).

Pros

The aquaculture industry is welcome in many of Canada’s coastal regions: it brings employment and investment to regions that have suffered through economic restructuring after declines in traditional fisheries and forestry (Young & Liston, 2010). Aquaculture can benefit the Canadian economy because a lot of fish farms can be in less populated regions where support to regional economic development is necessary (“The Canadian salmon aquaculture industry,” 1990). The market potential for salmon and aquaculture products in Canada is enormous due to its proximity to the United States. This is due to low transportation costs which guarantee Canada a competitive edge over countries like Norway who must transport across the Atlantic Ocean ("The Canadian salmon aquaculture industry," 1990).

Many stakeholder groups support aquaculture and for a variety of reasons, such as "food production, food security, [providing] significant employment/livelihood opportunities, and income generation" (De Silva, 2012). They may want to support and preserve the coastal way of life or reinvigorate the economy in different regions (Young & Liston, 2010). The aquaculture sector is responsible for "over 17 000 jobs" and approximately "90% of these jobs are in rural, coastal and Aboriginal communities across Canada" (Sarker et al., 2013). Some aquaculture systems even have a net overall positive impact on biodiversity and conservation, either directly and/or indirectly (De Silva, 2012). This is possible because aquaculture can provide relief for wild aquatic animals threatened by overharvesting and can conserve land by utiliing 'marginal' land that is not suitable for other industries like agriculture (De Silva, 2012). The industry may also be necessary to feed our growing world population and help mitigate starvation in certain areas.

Farmed salmon tend to utilize feed more efficiently than any other farmed animal. This is because salmon are cold-blooded: they don't expend energy to maintain a consistent body temperature. They also conserve energy as they can easily maintain their body position and movement due to living in water (Sarker et al., 2013).

Cons

As mentioned above, salmon aquaculture can occur in coastal regions struggling economically. This makes the industry seem welcome, but many others may see it as a threat to already weak traditional sectors and any emerging industries (Young & Liston, 2010).

The sustainability of the aquaculture industry and its impact on biodiversity have faced major criticism. The industry over-depends on dwindling natural resources like fish meal and fish oil (De Silva, 2012). Small, pelagic fish are harvested for feed which can disrupt the natural food chains (Sarker et al., 2013). Some argue that these fish might be consumed directly rather than being used to produce other fish (Sarker et al., 2013).

Another major issue seen in the industry is pollution. Environmentalists worry about salmon aquaculture sites and the accumulation of wastes like fecal matter and uneaten feed, and chemicals that leak into the surrounding marine environment (“The Canadian salmon aquaculture industry,” 1990; Young & Liston, 2010). These waste products can be released either directly or indirectly and there is limited capability to recover it (Sarker et al., 2013). There are many objections to the use of antibiotics and pesticides, as well as artificial colourants in the production of salmon (Young & Liston, 2010). These waste by-products can cause nutrient enrichment in the freshwater and marine ecosystems (Sarker et al., 2013). The chemical waste can remain as residual in the stock or wash off into the environment and it can be slowly degrading or non-degradable, as well as carcinogenic. These chemicals can be highly toxic to non-target organisms and can potentially bioaccumulate over trophic chains (De Silva, 2012).

A third issue in the industry that concerns Government officials is the transferring of diseases and parasites that could upset the natural balance of life in the area (“The Canadian salmon aquaculture industry,” 1990). Due to the high population density of many salmon farms, pathogens can transfer among captive fish easily (Young & Liston, 2010). These can enter the surrounding marine environment due to changing currents, excess use of chemicals, and even through escapes (De Silva, 2012). Escaped salmon worry fishermen who fear disease may transmit from farm to wild stocks, as well as they may harm the environment as they can potentially displace wild populations by competing for habitat, food, and even mating partners (“The Canadian salmon aquaculture industry,” 1990; Young & Liston, 2010). Farmed fish are also less adapted to life in the wild, and while they may not all survive, any potential interbreeding of farmed and wild stocks can cause a loss of genetic diversity (De Silva, 2012).

In the Atlantic regions, native salmon populations are critically endangered. There is fear around salmon farm escapes competing with these fragile wild stocks or altering the genetic pool through inter-breeding (Young & Liston, 2010). In the Pacific regions Atlantic salmon are ‘exotic’ and here the fear is that escaped fish can colonize Pacific waterways, pushing out naturally occurring species (Young & Liston, 2010). In both regions aquaculture treads on the issue of Indigenous rights. Many farms operate in spaces that are claimed as ‘traditional territories’ (Young & Liston, 2010). They can interrupt Indigenous fishing for food and livelihood. Sports fishers are concerned about nets and pens blocking access to their local fishing grounds. This concern is also shared by Indigenous communities who may rely on the marine environment.

Canadian Salmon Aquaculture Regulation

West Coast

Most salmon aquaculture operations are in freshwater lakes, which are a provincial resource and not a federal one (Government of Canada, 2020). However, highly lucrative salmon aquaculture grow-out operations are ocean-based and involve both the federal and provincial governments (giving provincial jurisdiction over natural resources, environment, and business licensing). Therefore, jurisdictional uncertainty and complexity define the Canadian salmon aquaculture industry (Young & Matthews 2010). A court ruling in 2009 (*Morton vs. British Columbia*) suggests that the federal government cannot delegate responsibilities to the province of B.C. However, after 2010, a salmon aquaculture agreement lays out the responsibility of both federal and provincial governments in Canada (Ministry of Agriculture, 2018). The salmon aquaculture facilities must comply with legislation like the Fisheries Act, Health of Animals Act, the Food and Drugs Act and the Species at Risk Act (Government of Canada, 2020). Each site a firm has must have a license, and renewal must be at the frequency in the conditions every six years for marine finfish like salmon (Government of Canada, 2020). Additional licenses are necessary for other salmon aquaculture-related activities like imports/transfers of fish. As of 2020, the Ministry of Agriculture has a new approach to salmon farm tenures. Starting in June of 2022, the Province will grant Land Act tenures only to fish farms that satisfy DFOs conditions of operations that will not negatively impact wild salmon stocks. They must negotiate agreements with the First Nations groups whose territories they operate (Ministry of Agriculture, 2018). The new agreement outlines responsibilities for both governments:

- DFO is responsible for the conservation and protection of fish and fish habitats and proper management and control of fisheries, including salmon aquaculture (Ministry of Agriculture, 2018).
- Canada is responsible for collecting data regarding the environmental performance of the industry in B.C. via its licensing activities (Ministry of Agriculture, 2018).
- The Ministry of Agriculture is the leader in B.C. for seafood industry development and strategic salmon aquaculture policy (Ministry of Agriculture, 2018).
- Ministry of Forests, Lands, Natural Resource Operations and Rural Development issues Land Act tenures, authorizing the use of Crown land and foreshore (Ministry of Agriculture, 2018).

- The Ministry of Environment and Climate Change Strategy issues permits for sewage discharge and pesticide use (Ministry of Agriculture, 2018).

Under the agreement:

- Canada may issue salmon aquaculture licenses under the Fisheries Act to undertake all salmon aquaculture activities in B.C. (Ministry of Agriculture, 2018).
- B.C. may issue land tenures under the Land Act for salmon aquaculture purposes (Ministry of Agriculture, 2018).
- Canada and B.C. will best harmonize their decision-making criteria and synchronize their decision-making processes (Ministry of Agriculture, 2018).

East Coast

Canadian federalism complicates aquaculture governance and regulation. In the Atlantic region of Canada, wild Atlantic salmon populations are declining precipitously, and several stocks are in danger and highly vulnerable (Young et. al., 2019). In Atlantic Canada, there are over 70 different species for farming (Atlantic Canada Opportunities Agency, 2021). The bulk of agriculture on the Atlantic coast, much like the Pacific coast, is Atlantic salmon (85%) (Atlantic Canada Opportunities Agency, 2021). The aquaculture industry is important to the East Coast as it employs ~35,000 people and generates over $2.5 billion in exports annually (Atlantic Canada Opportunities Agency, 2021).

In the Maritimes, New Brunswick (N.B.) has the largest salmon farming aquaculture industry in value (Flaherty et al., 2019). In N.B., salmon farming began in the Bay of Fundy and now accounts for over 90 sites (Flaherty et al., 2019). In Nova Scotia (N.S.), the aquaculture industry is also growing and becoming increasingly important due to its economic contributions (Flaherty et al., 2019). Interest in N.S. grows as fewer expansion projects are allowable in N.B. (Flaherty et al., 2019). After a 2013 moratorium and investigation into the industry, the provincial government drafted new legislation to manage aquaculture in the province (Flaherty et al., 2019). On Prince Edward Island (P.E.I.), the aquaculture industry comprises mainly of mussels and oysters.

The east coast provinces in Canada update their aquaculture legislation and regulations regularly (Fletcher, 2021). These provinces encourage the aquaculture industry to take an active role in creating an aquaculture policy (Young & Matthews, 2010, pg. 246). In 2019, N.B.

received Royal Assent for a new *Aquaculture Act*, N.S. revamped its own regulatory framework in 2015, Newfoundland and Labrador completely revised their policy in 2019, and P.E.I. has the intention of drafting a new Aquaculture Act (Fletcher, 2021).

New Brunswick

In N.B., the New Brunswick Department of Agriculture, Aquaculture and Fisheries (NB-DAAF) and DFO are the provincial and federal departments that lead aquaculture regulation (Manning & Hubley, 2016). A Memorandum of Understanding (MOU) in 1989 between the two departments lays out their responsibilities. The provinces license and lease aquaculture operations and both levels of government develop site allocation criteria (Manning & Hubley, 2016). In 2008, through another MOU, N.B. worked with N.L., N.S. and P.E.I. to create a sustainable aquaculture industry on the Atlantic coast (Manning & Hubley, 2016). In N.B., in 1988, the provincial Aquaculture Act was passed (Manning & Hubley, 2016). In 1991 N.B. adopted the General Regulation under the Act (Manning & Hubley, 2016). These were used until 2005, when a performance-based standard framework was introduced (Manning & Hubley, 2016). Since the year 2010, the industry in N.B. is also guided by two key policy documents: the New Brunswick Finfish Aquaculture Development Strategy and the New Brunswick Shellfish Aquaculture Development Strategy (Manning & Hubley, 2016).

Newfoundland and Labrador

In 1988 N.L. signed an MOU with the province and federal government to start its involvement in the aquaculture industry on the Atlantic coast (Manning & Hubley, 2016). The provincial DFO in N.L. has responsibility for “aquaculture licensing, inspections, enforcement, and development and extension services,” and the federal DFO is responsible for habitat protection (Manning & Hubley, 2016). Both have responsibility for “environmental protection, aquaculture science, site inspection, and fish health” (Manning & Hubley, 2016). N.L. is also a part of the 2008 Atlantic MOU, where all four provinces work collaboratively (Manning & Hubley, 2016). In 1988 N.L.’s provincial DFO introduced the Aquaculture Regulations Act. This Act aims to: “promote the development of aquaculture; secure the property rights of the industry; minimize conflicts with competing interests and uses and engage in cooperative decision making within the province and with the federal government” (Manning & Hubley, 2016).

Nova Scotia

In N.S., an MOU also outlines the aquaculture industry’s development between the federal and provincial governments (Manning & Hubley, 2016). N.S. leads on licensing and leasing, inspecting sites and compliance issues, and the management of fish health (Manning & Hubley, 2016). Both the federal and provincial governments are responsible for environmental management and monitoring (Manning & Hubley, 2016). N.S. is also a part of the Atlantic Coast MOU since 2008 (Manning & Hubley, 2016).

Prince Edward Island

Unlike the other provinces, P.E.I. does not have a “provincially-based regulatory framework for aquaculture” (Manning & Hubley, 2016). DFO is the primary authority (through sections 7 and 58 of the Fisheries Act) for managing P.E.I.’s aquaculture (Manning & Hubley, 2016). This authority dates to an MOU signed in 1982 and renewed in 1987 (Manning & Hubley, 2016). P.E.I.’s provincial department has some rights and obligations in the provincial Fisheries Act (Manning & Hubley, 2016). The Aquaculture Leasing Management Board (ALMB) is responsible for the overall management of aquaculture in P.E.I (Manning & Hubley, 2016). P.E.I. also participates in the 2008 Atlantic Coast MOU (Manning & Hubley, 2016).

LITERATURE REVIEW

Stakeholder theory and stakeholder management theory are the main theoretical frameworks I use in this thesis to analyze data from the sentiment analysis method (or content analysis method). The two theories investigate perspectives about salmon aquaculture in Canada. The theory of stakeholder management and the sentiment analysis method are critical to this thesis research to understand further the salmon aquaculture industry and the government and non-government institutions that work within this industry or face effects from the industry. As I explore marine salmon aquaculture, I need to define what aquaculture is in the context of this thesis. I focus mainly on *finfish aquaculture,* as salmon is a finfish.

This literature review covers the aquaculture controversy and why the industry is controversial, sustainable development of the sector, Indigenous perspective and knowledge systems and collaborative governance. These themes are relevant to the thesis as they explore the industry's positive and negative sides that help us understand why sentiment may shift to either the positive or negative side, depending on the time and the stakeholders.

Aquaculture Controversy

In Canada, DFO leads the management of coastal oceans and most marine resources (Silver, 2014). Aquaculture (a "catch-all term for a highly variable method of food production") is a significant contributor to global food production, but with this comes controversy (Young et al. 2019). The Canadian industry produces marine and freshwater species, and the provincial and federal governments continue to support the industry from as early as the 1980s (Young, et al., 2019). Salmon aquaculture is also "the most controversial subsector of the industry," It reflects the history of Canada's coastal and resource development and the unresolved questions surrounding the environment, development, rights, and governance (Young & Matthews, 2010, pg. 5, 228).

Canada wants the growth of aquaculture because it is a solution to some issues in the country such as a growth spurt for areas in isolation that are suffering economic hardship and to shift the declining workforce and re-establishing Canada's growth in the global seafood market (Young & Matthews, 2010 pg. 228). Canada's aquaculture industry saw its start in small-scale production and is now at the industrial scale, and with it comes all the issues typical of industrial food production (Milewski & Smith, 2019). The kinds of problems in the aquaculture industry are waste-product pollution of feces and food, chemical run-off from antibiotics, pesticides and veterinary treatments, issues of environmental quality surrounding farms like nutrient and organic loading, and transmission of pathogens from farm escapees (Milewski & Smith, 2019). There are even some human health concerns from bi-products of the run-off or chemical levels within the fish in farms (Milewski & Smith, 2019). The industry has issues with diseases like infectious salmon anemia and piscine reovirus, as well as sea lice outbreaks (Milewski & Smith, 2019). In the market, issues arise from increasing competition, price fluctuations, and the availability of sites and licenses due to moratoria by governments (Milewski & Smith, 2019).

In wealthier countries, the controversy surrounding aquaculture comes from the impact on wild stocks and degradation of habitat (Young, et al. 2019). In Canada, we see much the same case as environmental impacts have been the most consistent issue arising (Young, et al., 2019). There is also some regulatory overlap and complexity between Canada’s two different coasts, which is also a significant issue (Young, et al. 2019). Without aquaculture-specific legislation, there is considerable uncertainty in the realm of aquaculture (Young et al., 2019). In Canada, this occurs because governance typically falls under the federal *Fisheries Act* leading to uncertainty in the regulatory mix (Young et al., 2019). Because the government controls access, they have more authority for granting (or restricting) access to various user groups (Young et al., 2019). Within Canada, there is also the issue of distrust of some foreign involvement or ownership of aquaculture operations and the rights of Indigenous groups over their traditionally-used territories (Young et al., 2019). Though DFO claims through several narratives that aquaculture in Canada is entirely sustainable, the truth is that there is very little empirical evidence to support this claim (Milewski & Smith, 2019).

Sustainable Development of Salmon Aquaculture

The Canadian government assumes the sustainable development paradigm from the Brundtland report (Milewski & Smith, 2019). Sustainability indicators (SIs) aim to inform policy progress toward sustainability goals. The goals include a reference value (target, standard, norm, goal, benchmark) for measurement that indicates movement towards or away from an objective. It also provides the public with a measure of accountability for policy initiatives (Milewski & Smith, 2019). Environmental SIs for finfish aquaculture operations include the amount of resources used (e.g., water, energy, space, feed, and amount of raw marine ingredients), waste discharged (e.g., nitrogen, phosphorus, particulate organic matter, GHGs, metals), chemicals used (e.g., antibiotics, pesticides, hormones), disease incidence, fish escapees, genetic interactions, and biodiversity impacts; none of which DFO publicly reports on (Milewski & Smith, 2019). Canada's lack of progress on salmon aquaculture SI development is part of a broader trend involving governments devolving some aspects of public policy and decision-making to non-state actors (Milewski & Smith, 2019).

Finfish aquaculture proves to be contentious in the political and policy struggles as the industry moves from staples (wild fishery) to a post-staples (farm fish) resource sector (Rayner & Howlett, 2007). Without the inclusion and consideration of the First Nations peoples, environmental injustice will continue, and the industry will falter. How both the industry and First Nations groups and the public understand and perceive salmon aquaculture will require further in-depth studies and participation and a move beyond secondary research to in-person research (Flaherty et al., 2019). The inequitable processes and politics of regulating spaces and economies are a necessary starting point for researching the governance of oceans and coastlines and new marine activities (Silver, 2014)**.**

Indigenous Perspectives on Salmon Aquaculture

Salmon aquaculture governance is an essential aspect of the growth and survival of the First Nations groups. Smaller First Nations groups primarily inhabit areas where salmon aquaculture can help provide food security and alleviate poverty through economic development (Hishamunda & Ridler, 2003). However, critics argue that salmon aquaculture can harm food security through the reach of diseases like piscine orthoreovirus (PRV) or sea lice that can harm farms and wild fish (Slaughter, 2020). If these diseases kill and affect farm salmon, they can also harm wild salmon and hundreds of other species that rely on salmon in their food chains. In addition, diseases can harm other species, or if the stock numbers decline, enough species above them in the food chain will die as their food sources decline (Slaughter, 2020).

First Nations groups of Canada have a different lens through which they view the environment. Pacific salmon are core to the foundation of their social-ecological systems, and they are an integral part of Indigenous groups' food security, cultural practices, health, and economy (Atlas et al., 2021). They refer to their "knowledge of the land" rather than ecological knowledge from their perspective. The *land* is more than just the physical landscape; it includes the living environment (Berkes, 2018, pg. 5). Indigenous knowledge is not uniform across all Indigenous peoples. Thus, the term is often pluralized to "Indigenous knowledge**s,**" It is a way of being and living within the world (Reid et al., 2021). In academic literature, knowledge is 'Traditional

Ecological Knowledge (TEK), and there is no single Indigenous Knowledge (IK) system (Bingham et al., 2021). The difference between Indigenous and scientific ways of knowing is ontological, as Indigenous ways of knowing are about worldviews (Bingham et al., 2021). These definitions of 'indigenous knowledge' are shifting away from the concept of utility (how the knowledge is helpful to Western society) and reductionism, or how it offers "data" for analysis (Reid et al., 2021).

Traditional ecological knowledge is essential for collaboration with Canadian and provincial governments in salmon aquaculture governance. Approaches that can remedy power relations, respect differences, and uphold their unique strengths are necessary for this collaboration (Reid et al., 2021). It is "a way of knowing; dynamic, building on experience and adapting to changes" (Berkes, 2018, pg. 8). Characterization of the Indigenous knowledge systems is through their "embeddedness in the local cultural milieu; boundedness of local knowledge in space and time; the importance of community; lack of separation between nature and culture, and as a unique and irreplaceable place; and a non-instrumental approach to nature." (Berkes, 2018, pg. 11). By contrast, we denote Western scientific knowledge systems by "disembedded universalism, individualism, nature, culture and subject, object dichotomy, mobility, and an instrumental attitude (nature as a commodity) toward nature" (Berkes, 2018, pg. 11).

The reality is that the opposition to, and support for, aquaculture is quite complex. Much of the local understanding of the industry reflects on deep themes of Indigenous grievances on issues such as their rights and governance (Young & Matthews, 2010 pg. 71). Indigenous support for aquaculture cannot be a license for development: current Indigenous participation in aquaculture is "an assertion more than an endorsement" (Young & Matthews, 2010, pg. 72).

Collaborative Governance

Collaborative governance is a governing strategy developed over the last few decades (Ansell, 2008). The concept of collaborative governance refers to a range of practices for stakeholder engagement and co-governance (Young et al., 2020). It often means bringing multiple stakeholders together in common forums to engage in consensus-oriented decision-making (Ansell, 2008). This form of governance responds to the "failure of downstream institutions and the high price and politicization of regulation" (Ansell, 2008). Ansell defines collaborative governance as follows:

> "A governing arrangement where one or more public agencies directly engage non-state stakeholders in a collective decision-making process that is formal, consensus-oriented, and deliberative and aims to make or implement public policy or manage public programs or assets."
>
> (Ansell, 2008)

Collaborative approaches to addressing environmental challenges are global (von der Porten et al., 2015; Young et al., 2020). In the case of salmon aquaculture, public agencies like the federal government are often the initiators or instigators of collaborative governance. Still, to be collaborative, there must be participation by non-state stakeholders (Ansell, 2008). One important way individuals can self-organize collectively to govern things like natural resources is through a "coalition for collective action" (Baird et al., 2019). In this way, all individuals have an incentive to coordinate their behaviour amongst themselves and to share their opinions and thoughts (Baird et al., 2019). Decision-making power is shareable amongst different stakeholder groups, and those who can make decisions (those individuals or groups seeing the "most impact from the potential planning outcomes") make them (von der Porten et al., 2015).

Collaboration can never be consultative; both agencies and stakeholders must have two-way communication and influence (Ansell, 2008). A variety of terms are interchangeable with collaborative governance. Those terms are: "participatory management, interactive policy-making, stakeholder governance, and collaborative management" (Ansell, 2008). Critics of the concept of collaboration or co-management argue that it falls short of their "ideal processes and goals" (Young et al., 2020). Nadasy (2007) states that a significant injustice in co-management comes from the fact that local groups must "agree to the rules of the game," and those rules are advantageous to traditional authorities (Young et al., 2020).

In Canada, there are three significant problems in governance, which in Young & Matthew's (2010) paper are the "triple pressure" (Young & Matthews, 2010 pg. 232). The first issue is economic, the second environmental, and the third problem is legitimacy. The globalization of the economy is putting competitive pressure on Canada's aquaculture industry (Young, 2010, pg. 232). The environment is increasingly becoming a major political issue in Canada as we see more interest in climate change and environmental protection (Young & Matthews, 2010, pg. 232). The third issue of legitimacy stems from the fact that governments are having a hard time legitimizing the aquaculture industry, as well as their “own policies and regulations” (Young & Matthews, 2010, pg. 232).

Collaboration and use of Traditional Ecological Knowledge

The issue with collaboration between First Nations groups and Canada is the lack of understanding of the knowledge and these differing knowledge systems. The assumption that Indigenous peoples are stakeholders in cases taking place on their lands is problematic in and of itself (von der Porten et al., 2015). From the perspective of Indigenous communities, stakeholder-framed approaches are not the only alternative for collaboration (von der Porten et al., 2015). Government departments often require the inclusion of TEK in policy and legislation without proper consultation or engagement strategies, in unrealistic time frames and without financial support (Berkes, 2018, pg. 17). The Western view needs to note TEK documentation before it is “valuable” information. This TEK can then integrate into Western science processes and frameworks, thus assimilating Indigenous knowledge (Berkes, 2018, pg. 17). This knowledge is then a part of the public domain, meaning that any person or corporation has access to it as soon as it leaves the community (Berkes, 2018, pg. 40). Therefore, collaboration always needs to be participatory and include TEK. A barrier to collaboration is that TEK is only conservable *in situ.* It means that much of TEK is not removable from its community and context as it no longer makes sense (Berkes, 2018, pg. 35).

Twenty First Nations groups have funding and priority access to marine tenure leases from B.C.’s provincial government through treaty negotiation-related Memoranda of Understanding between the 90s and early 2000s. First Nations did not receive treaties (Silver, 2014). Instead, commercial fishing rights are in ‘harvest agreements’ that may seek to enhance First Nations' participation in fisheries but fall outside the constitution that final treaty agreements protect (Harris & Millerd, 2010). Moreover, the possibility for collective ownership over and sovereign governance authority in tracts of territorial ocean space appears to remain altogether unaddressed (Silver, 2014).

THEORETICAL CONCEPTS & FRAMEWORKS

Stakeholder Theory

For businesses in the past, "doing business" was buying raw materials from suppliers, turning those materials into products, and selling them to customers (Freeman, 1984, pg. 5). Figure 1 depicts the firm's "Production View" (Freeman, 1984 pg. 5).

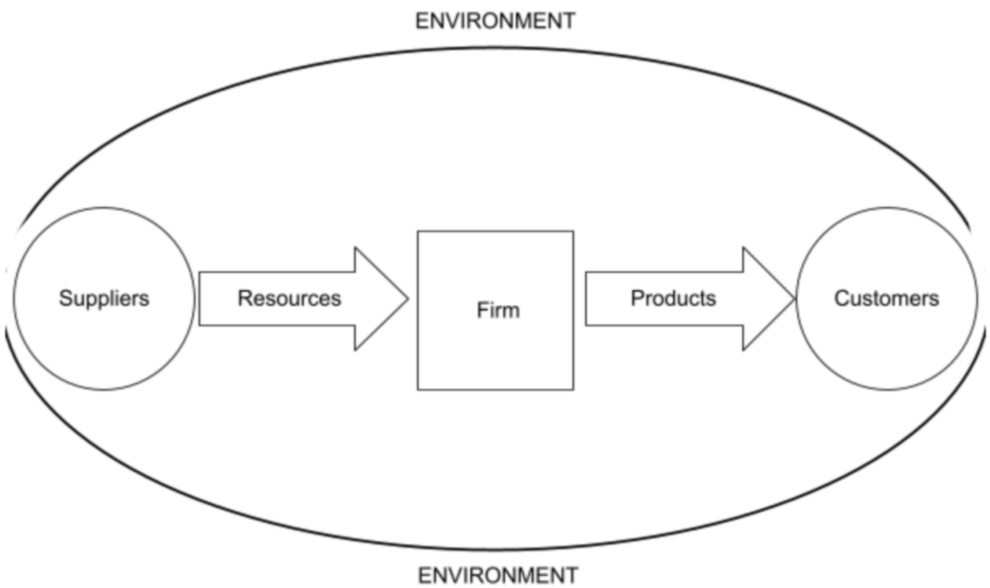

Figure 1. The Production View of the Firm (Freeman, 1984 pg. 5)

Stakeholders are vital to a business or project as they are the groups and individuals with interest in the activities and outcomes of the company or project or on whom the firm is reliant to achieving its objectives (Freeman et al., 2018, pg. 1). The use of the term “stakeholder” allows businesses to see these groups as having a “stake” (Freeman, 1984, pg. 45). There is no universally accepted definition of a stakeholder. However, there are many common attributes between the different iterations of the report to examine naturally occurring events where the researcher has no authority over them (Leopkey & Parent, 2015). These attributes include aspects of interdependence, affecting the organization or those the organization is affecting, and a sense of interest in examining naturally occurring events where the researcher has no authority over them (Leopkey & Parent, 2015). In addition, stakeholder connotes “legitimacy” because these groups can affect the direction of the business (Freeman, 1984, pg. 45). Researchers often categorize stakeholders by primary/secondary (see Carroll 1993, Freeman 1984), actual/potential (see Clarkson et al., 1994), internal/external (see Jones 1995), fiduciary/non-fiduciary (see Goodpaster 1991), necessary/contingent and compatible/incompatible (see Friedman and Miles 2002) (Crane, 2011). Often stakeholders are owners, financiers, stockholders, customers, employees, suppliers, and competitors, as these are the primary groups identifiable by an economic relationship to the firm. In contrast, the secondary group of stakeholders are community members and advocates that depend on the environment of the company at the time (Crane, 2011). The primary stakeholders typically include: "customers, employees, suppliers of tangible goods and services, suppliers of capital, and the communities in which the firm operates" (Freeman et al., 2018, pg. 1). Other typical 'secondary' stakeholder groups are government officials and regulators, special interest groups, NGOs or ENGOs, media, unions, and even competitors (Freeman et al., 2018, pg. 1). Primary stakeholders are typically those with a financial stake in the businesses that often contribute to their overall success. A secondary stakeholder may focus more on what the company is doing and how that may affect the community in which it operates. Figure 2 shows the relationship between primary and secondary stakeholders, with the firm in the center.

The stakeholder theory is key to this research as I use it to explore the relationships between the industry and its stakeholder groups to determine their sentiment toward the industry. With this understanding, firms can better decide how to include stakeholders, and perhaps better understand their needs. Stakeholders, on the other hand, can use research to see how to have their needs met and how to engage with one another and the industry to induce the changes they want to see.

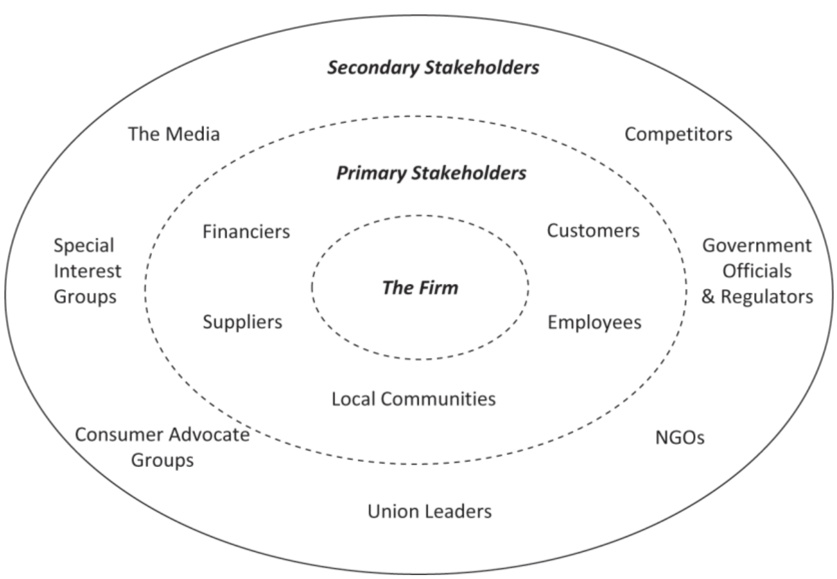

Figure 2. A Basic Stakeholder Map (Freeman et al., 2018, pg. 16)

The stakeholder perspective, or theory, first appears in a book in 1984 by author Edward Freeman, *Strategic Management: A Stakeholder Approach* (Freeman et al., 2018, pg. 2). Freeman explores "various literature including corporate planning, systems theory, and corporate social responsibility to develop a stakeholder approach" (Laplume & Litz, 2008). Stakeholder theory is "effective in offering normative and instrumental grounding for inclusion of stakeholders into managerial decision making" (Crane, 2011). Stakeholder theory asks for whom we create value (Freudenreich et al., 2019).

By the 1970s, the stakeholder concept surfaces in several places in the strategic planning literature (see Figure 3 below) (Freeman, 1984 pg. 33), and since the mid-1980s, this concept has been more and more popular in strategic management (Freeman et al., 2018, pg. 2). The stakeholder perspective is a different way of understanding the link between how companies and people create value and trade with one another in a world with little stability and certainty (Freeman et al., 2018, pg. 1). The concept of stakeholder theory explores the idea that shareholders and their values are significant but not the only group critical to the success of a business (Freeman et al., 2018, pg. 2). The idea is that stakeholders' social and economic identities together provide a better model of the relevant stakeholder groups (Crane, 2011). The ideal principle in stakeholder theory is that relationships exist whereby all the firm's key stakeholders are "winners" (Freeman et al., 2018, pg. 3). In the case of sustainability-oriented frameworks, the theory can also include ecological and social outcomes that benefit other stakeholders (Freudenreich et al., 2019). This is key for the aquaculture industry, especially on Canada's west coast, where the industry is not very popular. They can use this theory to try and benefit all their stakeholders and build better relationships so that they can have further support for the industry.

Many researchers add to Freeman's original stakeholder theory (Torelli & Furlotti, 2020). In addition, some include other economics concepts (agency theory, transaction economics, and team production theory), as well as insights from behavioural science and ethics (Torelli & Furlotti, 2020). This way of examining stakeholder theory focuses on the relationships between stakeholders and the firm and hypothesizes that trust and cooperation are crucial to solving opportunistic problems. Firms that do so will have a competitive advantage over those that do not use such criteria (Jones, 1995, pg. 432) (Torelli & Furlotti, 2020).

"Stakeholder Management" as a concept refers to the "necessity for an organization to manage the relationships with its specific stakeholder groups in an action-oriented way" (Freeman, 1984, pg. 53). Freeman's approach here is inherently 'managerial.' It is a theory (or framework) about "managerial behaviour, first, and organizational behaviour, second" (Freeman, 1984 pg. 43).

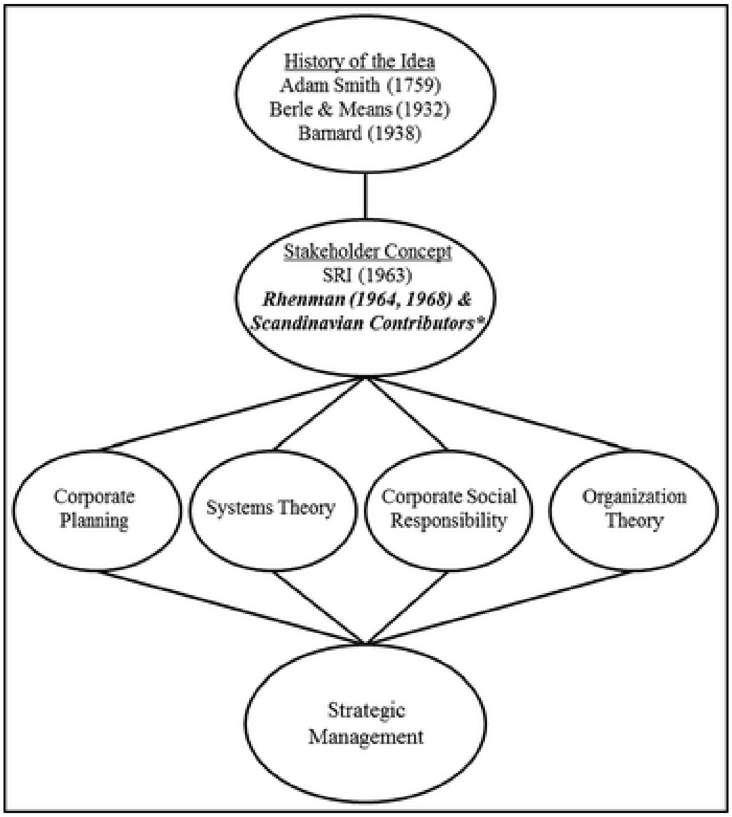

Figure 3. A History of the Stakeholder Concept (Freeman, 1984 pg. 32)

Stakeholder management sits on a "moral foundation that includes respect for humans and their basic rights, integrity, fairness, honesty, loyalty, freedom to choose, and assumption of responsibility for the consequences of the actions that a firm takes" (Freeman et al., 2018, pg. 3). A stakeholder approach enables a business to identify its relevant stakeholders and develop the capability to deal with diverse stakeholder groups (Freeman et al., 2018, pg. 13). Allowing for the broader inclusion of multiple stakeholders will enable businesses to avoid problems with the companies' primary shareholder approach. The only concern is making money to keep the shareholders happy (Freeman et al., 2018, pg. 13). Using a stakeholder approach encourages greater moral accountability and helps to resolve the conflict between shareholders and stakeholders by creating value for everyone (Freeman et al., 2018, pg. 13). Value creation entails various activities by different groups/individuals in the businesses network (Freudenreich et al., 2019). Value is different for each stakeholder and may also be a combination of different types of value (Freudenreich et al., 2019). Each stakeholder plays a vital role in the value creation process (Freudenreich et al., 2019). A business's value for its stakeholders is not necessarily only an economic one. It can provide various other benefits such as "personal development, affiliation, freedom to choose, esteem and happiness" (Freeman et al., 2018, pg. 5). A business can also gain a particular reputation by treating its stakeholders well. This reputation can be influential to both existing and potential future stakeholders, and it is impossible to build a model without good relationships with both internal and external stakeholders (Freudenreich et al., 2019) (Freeman et al., 2018 pg. 7).

The stakeholder approach argues that stakeholder-oriented management enables managers to perform four crucial activities better (Freeman et al., 2018, pg. 10). These activities create value, and innovation, address the inclusivity and interconnectedness of various groups/individuals and better address ethical issues (Freeman et al., 2018, pg. 10). Stakeholders simply a two-way relationship between the stakeholder and the business when the stakeholders interact and the company sits in the “middle of the value-creating network” (Freeman et al., 2018, pg. 15).

For each business, it is necessary to determine the critical stakeholders. However, identifying stakeholders is vague and superficial, limiting the use of stakeholder theory (Crane, 2011). The business needs to understand the identifications that drive constituency membership, as stakeholders have several generic economic functions like consumption, investing, and supplying (Crane, 2011). A business can group stakeholders into broad categories as a useful starting point (Freeman et al., 2018, pg. 18). All stakeholders may not share the same interests and thus are not entirely homogenous between these groups (Freeman et al., 2018, pg. 18). Categorization of stakeholders can occur on the grouping of ages, the areas in which they live, or other types of demographic and sociocultural factors (Freeman et al., 2018, pg. 19). Stakeholders are not always consistent; they change regularly with new stakeholders joining and existing stakeholders leaving (Freeman et al., 2018, pg. 19). Stakeholders are ultimately people. They have many “emotions, biases, desires, needs, interests, differing experiences, cognitive capabilities, perspectives, skills, and backgrounds (Freeman et al., 2018, pg. 21). For example, a stakeholder as an employee of the business may have specific values and expectations. Still, a mother in the community may have other values or interests that influence her (Crane, 2011). To properly understand the critical stakeholders to its business, its managers must correctly classify constituencies across both economic and social identities (Crane, 2011).

Using a cross-mapping of financial roles and social identities, a grid (Figure 4) below can identify the traditional stakeholders versus their social identities (Crane, 2011).

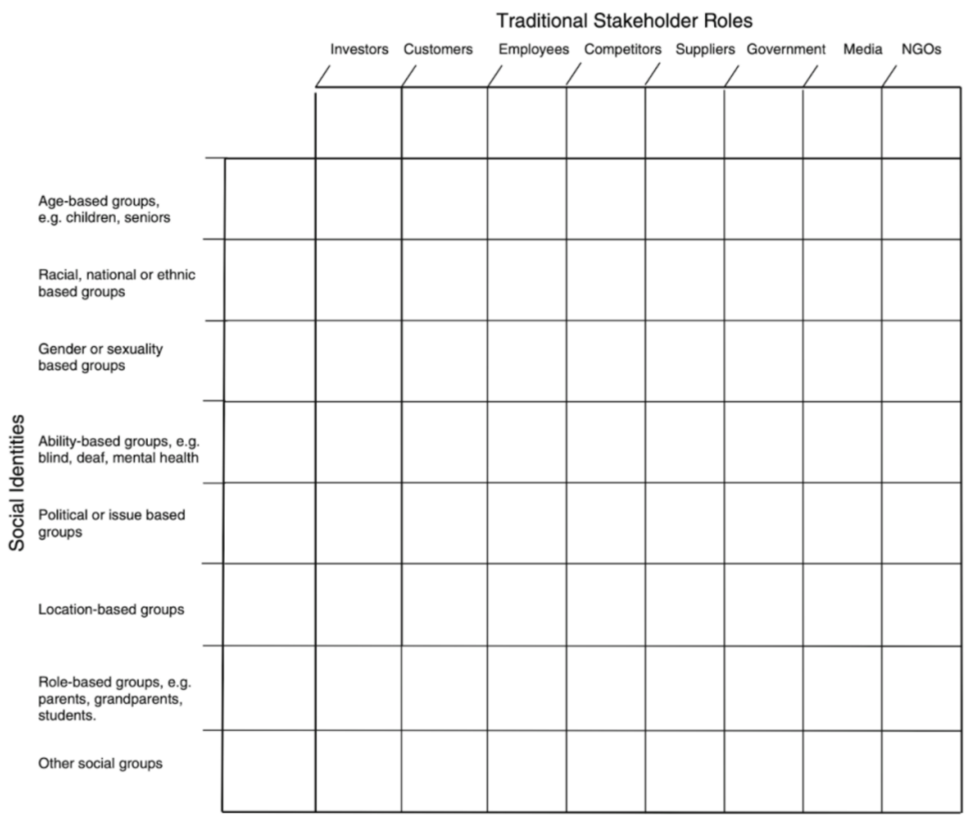

Figure 4. Stakeholder and social identity group cross-mapping (Crane, 2011)

Businesses that manage their stakeholders tend to display certain types of behaviour. Often, they show integrity and are trustworthy; their words match their actions. They often care about the welfare of their businesses' stakeholders and realize that all their business actions should in some way create value for stakeholders. They tend to be open and engage stakeholders (both primary and secondary) meaningfully and often. A business managing its stakeholders will try to align the interests of several stakeholders groups over time instead of "trading off the interests of one stakeholder against another." (Freeman et al., 2018, pg. 22). A stakeholder-oriented business is constantly creating additional value. This type of business is essential for stakeholders, as those without power must rely on the business's trustworthiness to satisfy any fairness obligations (Greenwood et al., 2010). It is crucial to the company as this value is available to invest in stakeholders, allowing additional weight in the next business cycle (Freeman et al., 2018, pg. 29). If the aquaculture industry can display this type of behaviour with its own stakeholders, better relationships can be created and nurtured to support the whole industry.

Unfortunately, stakeholder theory does not look at issues of power dynamics between organizations and different stakeholders, which often account for the differences in outcomes that the stakeholders experience (Greenwood et al., 2010). Organizational trust refers to "the trust between individuals, groups of individuals, and the organization as an entity in and of itself" (Greenwood et al., 2010). Trustworthiness is vital to the moral treatment of stakeholders in the organization–stakeholder relationship (Greenwood et al., 2010).

Whenever a business or a manager starts to say that a group of stakeholders is irrational, they should instead substitute this with "I do not understand that stakeholder's point of view" (Freeman, 1984, pg. 133). The managers use stakeholder Behavior Explanation in these types of situations. They view themselves from the stakeholder's place and try to empathize with their position and understand their point of view (Freeman, 1984 pg. 133). By better understanding the external environment of the group, the business, or the manager, one can see what external forces and pressures act upon that specific stakeholder (Freeman, 1984, pg. 134).

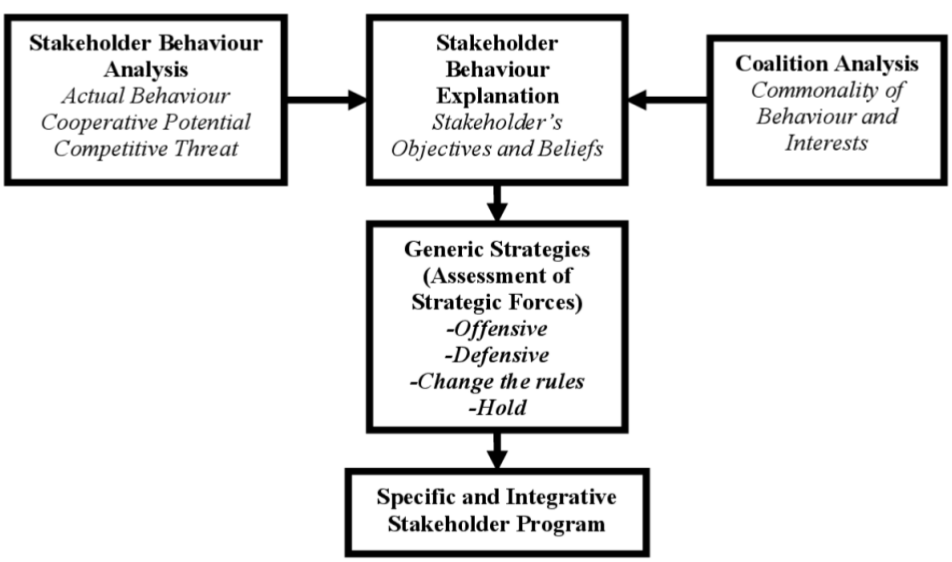

Figure 5. Stakeholder Strategy Formulation Process (Freeman, 1984 pg. 131)

Unhappy stakeholders can be highly detrimental to a business. Those with substantial social sway can influence negative actions against the company, such as boycotts, walkouts, strikes, and reductions of share prices. They can even affect the loss of contracts with other stakeholders (Freeman et al., 2018, pg. 37). For management, it may be necessary to identify stakeholder groups and determine their behaviours or possible future behaviours to determine if they will either create value or be detrimental to the business (Freeman et al., 2018, pg. 39). This identification is made by having management explore the behaviours that best describe the company and the stakeholder (Freeman et al., 2018, pg. 39). Management should look first at a particular stakeholder's actual or observable behaviour (Freeman, 1984, pg. 132). Control may then look at the stakeholder's cooperative potential, which are behaviours that "could be observable in the future that would help the firm achieve a higher objective" (Freeman et al., 2018, pg. 40) (Freeman, 1984, pg. 132). The last category is to look at 'competitive threat,' which may be harmful or threatening behaviour; and determine what actions stakeholders might take that would reduce the amount of value the business creates (Freeman et al., 2018, pg. 40), (Freeman, 1984 pg. 132).

Freeman's book *Stakeholder Theory: Concepts and Strategies* ask five questions that can help a business understand the perspective of its stakeholders. These questions are:

1. What are this stakeholder's main interests? How do we affect these interests? How do these interests affect us (Freeman et al., 2018, pg. 41)?
2. Who are the groups and individuals who can affect these stakeholders? Who are the stakeholders? Moreover, what is the stake (interest) (Freeman et al., 2018, pg. 41)?
3. What do the members of this group probably believe about us? What assumptions are they making? What assumptions do we make about them (Freeman et al., 2018, pg. 41)?
4. What are the natural coalitions that could occur? Where are the joint interests? What do the stakeholder and we have in common? What are the significant points of conflict (Freeman et al., 2018, pg. 41)?
5. What might cause a stakeholder to engage in more cooperative behaviour? More harmful (Freeman et al., 2018, pg. 41)?

By analyzing the cooperative potential versus the strategic threat of stakeholders, a business can determine "the potential of a stakeholder to affect how a firm creates value" (Freeman et al., 2018, pg. 51). Identifying stakeholder contributions asks: "What can this stakeholder do or provide to help the firm create more value?" (Freeman et al., 2018, pg. 44). Figure 5 shows that businesses typically have four ways to approach their stakeholders. The first method is to ignore the stakeholders. The second method is to improve their public relations with them. The third method of interaction is to have implicit negotiations or have good engagement, dialogue, and negotiation with stakeholder groups, where one can consider concerns to formulate strategic programs (Freeman et al., 2018, pg. 45), (Freeman, 1984, pg. 167). Finally, if there are no proper communication channels between the business and the stakeholder, the public relations approach can be suitable (Freeman et al., 2018, pg. 53). The PR approach is typically a one-way communication system, whereas the communication process with stakeholders should be two-way to ensure meaningful results (Freeman, 1984 pg. 166), (Freeman, 1984 pg. 167).

Ignore the Stakeholder

-Do nothing
-Allocate no resources

The Public Relations Approach

-Tell the company story
-Opinion leader communication
-Image-building

Implicit Negotiation

-Best estimate of stakeholder position

Explicit Negotiation

-Two-way communications
-Informal negotiations
-Setting and turf
-Proposal-response-compromise cycle
-Unilateral action
-Win-win solutions

Figure 6. Transaction Process for Stakeholders (Freeman, 1984 pg. 165)

If the stakeholder and the business's objectives are different, there are two options: a 'defensive' or a 'hold' strategy (Freeman et al., 2018, pg. 54). Defensive stakeholders are not very helpful but can take steps to prevent the firm from achieving its objectives. (Freeman, 1984 pg. 142). A "defensive" stakeholder management strategy is "appropriate for stakeholders with low cooperative potential, but that poses a large potential strategic threat" (Freeman et al., 2018, pg. 54). Offensive stakeholders can help achieve objectives but pose a minor relative threat. (Freeman, 1984, pg. 142). A "hold" strategy is suitable for stakeholders that are "low on the strategic threat, and cooperative potential-they can do relatively little harm or offer only a little help" (Freeman et al., 2018, pg. 55).

If a business has a well-designed stakeholder-based system, it can deal with uncertainty (Freeman et al., 2018, pg. 67). A company will be able to determine if it allocates too much value to anyone stakeholder or if it does not have enough to invest in future value-creating activities (Freeman et al., 2018, pg. 67). With the principle of fairness in mind, stakeholders should receive value from the business commensurate to how much they add to the value-producing processes of the company (Freeman et al., 2018, pg. 68). The main argument for this new way of thinking about and interacting with stakeholders is that “stakeholder management is about making money and creating value for everyone” (Freeman et al., 2018, pg. 69). If businesses can “begin to think in terms of how to serve stakeholders better, the more likely [they] will be to survive and prosper over time” (Freeman, 1984, pg. 80). The stakeholder concept is misleading yet straightforward. It is simple in that it can be easy to identify those stakeholders affecting the firm or those stakeholders whom the firm affects (Freeman et al., 2018, pg. 246). However, it is misleading that managing relationships with them is easy (Freeman et al., 2018, pg. 246). Businesses need to create relationships with crucial aquaculture industry stakeholders, then they can deal with uncertainty and see where they allocate value. If the value is understood, it can be created for everyone involved.

Sentiment Analysis

Sentiment analysis (or opinion mining) is a method in natural language processing (Hutto & Gilbert, 2014). It is a software-assisted process for extracting people’s feelings, opinions, and thoughts from their text data using Natural Language Processing (NLP) methods (Öztürk & Ayvaz, 2018) (Ferreira et al., 2019).

Analysis relies on data mining techniques and NLP to find, retrieve, and refine information/opinions from extensive and significant text sources (Ferreira et al., 2019). In addition, the analysis can analyze the emotional polarity of negative, neutral, and positive emotions (Mustaqim et al., 2020). To calculate a sentiment percentage, use the proportion of tweets with a specific sentiment (i.e., positive) among all the other tweets (Anwar Hridoy et al., 2015).

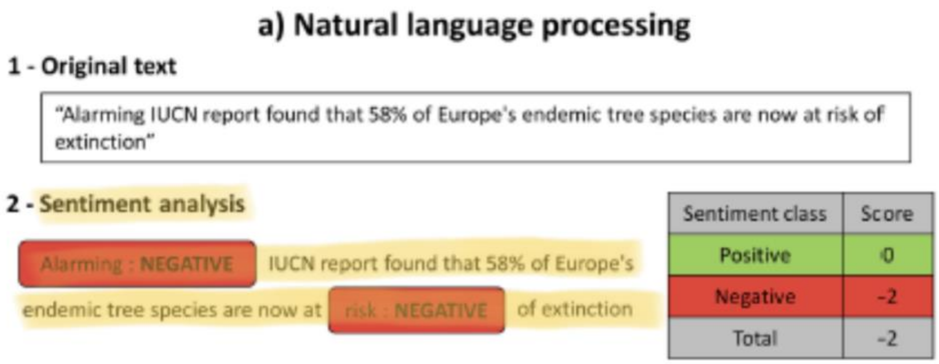

Figure 7. Example of the Process for Natural Language Processing (Correia et al., 2021)

Using NLP methods like sentiment analysis allows the extraction of quantitative information in texts and the sentiments about them (Correia et al., 2021). Figure 7 above shows text processing using specific sentiment analysis tools. In this example, the device scores each word on whether it has a negative or positive sentiment, and then the 'sentiment score' is the sum of these scores. Neutral words like "report" and "Europe" are given a score of 0. In Figure 7's example, the negative words are "alarming" and "risk." This example does not have any positive words, so the sum of scores is -2. Finally, VADER normalizes the compound score so that it lies between -1 (most extreme negative) and +1 (most extreme positive) (Singh, 2021). The closer the score is to +1, the higher the text positivity, and the closer this score is to -1, the lower the test positivity and the higher the negativity.

Many systems and programs analyze data from Twitter. Several different lexicons are useful in sentiment analysis, depending on the research and researchers' needs. The lexicon approach is an unsupervised method, where the text data are in predefined sentiment classes. Researchers can calculate the sentiment score(s) of the text from the lexicon (dictionary consisting of words and their corresponding sentiment scores) (Öztürk & Ayvaz, 2018). Lexicon-based methods are a model for determining the polarity of the text data (Öztürk & Ayvaz, 2018). This approach is portable and easily updatable where and when necessary (Öztürk & Ayvaz, 2018).

Sentiment Analysis and Stakeholder Theory

The use of sentiment analysis and stakeholder theory is this research's cornerstone. *Sentiment analysis* is a methodology that employs protocols for collecting and reducing data to help analyze large quantities of data (Laplume & Litz, 2008). In addition, sentiment analysis can be quantitative, like looking at correlations, trends, or differences over time, or qualitative to identify themes and elaborate theories (Laplume & Litz, 2008).

In Wood's 1991 paper, he suggests that in stakeholder theory, "corporations act in response to stakeholder desires, either in a preventive or a proactive way" (Torelli & Furlotti, 2020; Wood, 1991). The main idea of stakeholder theory is to create shareable value. Stakeholder engagement is essential to allow the firm to properly understand the needs and expectations of each stakeholder group, allowing for effective policies and reporting (Torelli & Furlotti, 2020). Without direct and meaningful stakeholder engagement, companies cannot employ well-targeted communication. Therefore, firms need proper engagement or cannot implement processes that consider all stakeholders' relevant aspects (Torelli & Furlotti, 2020).

Social media offers firms a chance to target, mobilize and interact with their stakeholders (Anagnostopoulos et al., 2017). A shift in recent years moves the focus from pure management of multiple stakeholders to engagement and interaction of various stakeholders in a relational view (Anagnostopoulos et al., 2017). Social media provides firms with new directions for their relationship-building in a unique environment that allows them to "create brand communities, conduct market research, carry out strategic communication campaigns or even achieve behavioural change (Anagnostopoulos et al., 2017). Using Twitter allows the firm to "go beyond a one-way dissemination of as is the case with other, more 'static,' means of communication, such as reports, websites, and e-newsletters" (Anagnostopoulos et al., 2017). Tailoring Twitter content to address issues that are relevant to stakeholders can either strengthen or initiate such relationships and partnerships (Anagnostopoulos et al., 2017). Twitter allows the company and researchers to examine "naturally occurring events," which is advantageous because they can see their industry, see how they discuss it, and see who is discussing it (Leopkey & Parent, 2015).

RESEARCH PROBLEMATIC

Research Advantages of Twitter scraping

Twitter is unique from other social media sites as it allows business owners, professionals, and the average user to reach an audience and engage with one another in diverse ways (Opeyemi, 2021). Data from Twitter serves as a “massive repository of true human behaviour and choice representations; and analyzing this data allows companies to understand customer feelings about ongoing trends, providing them with a platform for staying up to date with dynamic market demands” (Verma, 2021). Twitter users are 38% more likely to post their opinions about brands and products than other users on other social media platforms (Opeyemi, 2021). It is helpful because there is a lesser chance of bias as users express their opinions without prompting (Curran et al., 2011).

Social media creates virtual bonds among users, in which people express opinions and develop relationships through posts, comments, messages and likes. Social media allows approximately 2.4 billion web users to share their thoughts, feelings, and ideas with other people instantly and easily (Ignatow & Mihalcea, 2019; Öztürk & Ayvaz, 2018). Twitter represents a great mix of primary source information, and more users mean there is more and more data to access every year (Kirelli & Arslankaya, 2020). Twitter offers vast, representative, and searchable databases from millions of users that update in real-time (Kinzie, 2019) (Daume, 2016). These databases mean that data collection is less labour-intensive, time-consuming, and costly, making research accessible to everyone (Edwards et al., 2021). For OSINT, Twitter is not easy to use, as it can be challenging to search and parse vast amounts of data (Kinzie, 2019). However, Twitter is an easily accessible information stream that can provide information and ambient trends in a textual context that may not be available elsewhere (Daume, 2016). Web stats from Geekwire in 2012 suggest there are approximately 5 million terabytes of data online, and 20% of that is textual (Ignatow & Mihalcea, 2019). Moreover, providing near-real-time access to public posts through the API makes Twitter a suitable platform for large scale real-time opinion mining (Öztürk & Ayvaz, 2018)

Twitter can offer personal insights and observations from regular users, often avoiding the bias that can be unavoidable when doing other social research (Kinzie, 2019). Tweets are reliable data sources because users will tweet about anything and everything, even using hashtags and keywords to make identifying relevant data simple (Anwar Hridoy et al., 2015). The data from this can contain much valuable information like habit patterns, opinions and even the mental or emotional state of the writer/speaker that can be helpful for decision making (Ignatow, 2018; Mustaqim et al., 2020). As social media and the use of the internet become more widespread globally due to better quality, reliability, and coverage, data will improve as web crawling methods grow (Jarić et al., 2021).

Twitter offers a 'Business Model,' which is another way for businesses to utilize social media. Twitter's business model aims to profit and provide a structure for businesses to advertise and incorporate all their third-party partners (Curran et al., 2011). Curran et al.'s paper mention four strategies to use on a service like Twitter: direct, indirect, internal, and inbound signalling (Curran et al., 2011). The natural approach focuses on marketing and public relations. The indirect method is the engagement of employees with the community to build links. The internal strategy tends to ignore the general parts of Twitter instead of using it as a service for internal communication too, for the ability to share knowledge (Curran et al., 2011). Finally, inbound signalling is for businesses that do not want to participate in Twitter but understand its benefits (Curran et al., 2011).

Twitter businesses and users can use Twitter in a variety of ways. Twitter already provides firms with the ability to obtain and analyze data from multiple channels (Chong et al., 2017). Twitter is a vital information source for sentiment analysis applications (Asghar et al., 2018). For marketing purposes, it is possible to follow any trending hashtags or words/phrases to see what issues people are having. Businesses can directly market their advertisements to individual users (Opeyemi, 2021). Some companies may use social media to directly connect with consumers or collect feedback on their products and services (Opeyemi, 2021) (Curran, 2011). Companies can comment on trending topics, take a stance on specific issues, or join in conversations with their customers (Opeyemi, 2021). Twitter offers a broad spectrum of data that can be useful to many different stakeholders. This thesis looks at the sentiment of various stakeholders toward salmon aquaculture over time and determines if the sentiment is typically more negative or positive.

iEcology/Culturomics

Culturomics and iEcology are emerging fields of research that mine digital data. The methods of Culturomics focus on the "study of human culture through the quantitative analysis of large bodies of digital data" (Jarić et al., 2020). Conservation culturomics "aims to analyze the digital data [people create] to provide novel insights on human–nature interactions for conservation" (Correia et al., 2021). iEcology is an "approach which encompasses the use of software tools for discovering patterns in the natural world using data from digital sources" (Edwards et al., 2021; Jarić et al., 2020). Since iEcology and culturomics use available digital data, it can be far less costly than field sampling and social surveys. While these methods may not replace traditional field studies, they are an effective tool for preliminary research screening and ID of priority areas to focus on (Jarić et al., 2020). Digital content for such research comes from multiple sources and includes one or more data formats such as text, images, and videos (Correia et al., 2021). Unfortunately, iEcology and culturomics in aquatic realms has limitations and faces more significant challenges (Jarić et al., 2020).

Metrics	*Description*	*Example metrics*
Volume	absolute number of items (e.g., web pages, videos, and news items) that constitute the corpus	number of web pages number of videos
Frequency	relative frequency with which entities and concepts are represented within items of the corpus	word frequency in texts frequency of entity representation in images
Sentiment	polarity, intensity, or type of sentiments and emotions expressed in the corpus or in engagements with the corpus	emotions expressed in news images sentiment polarity of social media posts
Context	items associated with an element in the corpus	word or topic associations temporal or geographic context in which an element appears
Interest	number or proportion of searches, shares, and likes associated with the corpus	number of internet searches number of social media shares
Discussion	number of discussions, comments, or edits to elements of the corpus	number of comments to news number of users editing digital encyclopedias

Figure 8. Examples of metrics commonly used in culturomics research (Correia, 2021)

RESEARCH METHODS

This thesis is an inductive study, and the method is ‘sentiment analysis’ through the mining of Twitter data. The thesis analyzes the broad public conversation rather than being a systematic review of the literature. It looks at the state of the general discussion around salmon aquaculture and its stakeholders. I have used keyword searches of the term ‘aquaculture’ on the social media platform Twitter from 2006 to 2021. The initial download of data had 536,988 tweets. After this, processing occurred to remove any tweets that were retweets, did not have a user, were not in English, did not contain the word 'aquaculture,' or did not have a user bio. Once the VADER analysis was completed after processing, there was a further removal of data, which removed any neutral (0 scores) tweets as they are not necessary for answering the thesis questions. It is worth noting that "neutral” does not always indicate a lack of either positive or negative sentiment. Rather, they are tweets that may mention the keyword ‘aquaculture’ in passing, or the number of positive words may balance with the number of negative words. These tweets are often meant to inform rather than express the users’ opinion. These steps left me with 273,319 individual, unique tweets.

This thesis research is both qualitative and quantitative. The theoretical framework in this study is stakeholder theory. The research methods and tools in this thesis are Twint which allows for web scraping, VADER, which allows for sentiment analysis of the data, and the Pandas code framework and the Google Colab notebooks to allow for data processing and analysis. Data will facilitate addressing the research questions.

Twint

Twint is a “Twitter scraping & OSINT tool that does not use Twitter’s API, allowing you to scrape a user’s followers, following, tweets, and more while evading most API limitations” (Poldi, 2021). The benefit of using Twint rather than coding something through Twitter’s API (Application Programming Interface) is that it can fetch all Tweets rather than Twitter’s API limit of ~3200 tweets (Poldi, 2021). The initial setup is quick and anonymously usable, without the need for a Twitter account. There are also no rate limitations, as Twitter limits scrolls while browsing users’ timelines.

Twint utilizes the search operators that Twitter must allow for scraping tweets from specific users with hashtags or topics trends (i.e., keywords). This method works in queries to find

Twitter users' followers, tweets they may like, or a list of whom they follow. Many variables like when a tweet was sent, or location play a factor in the data's usefulness in research. Tools like Twint have combinable search filters to create databases of precise information pertinent to specific research (Kinzie, 2019).

The keyword "aquaculture" identifies which tweets to scrape from Twitter. All data from Twitter's inception in 2006 to August 2021 is available for processing. However, there is some overall data loss: for example, when removing all non-English tweets or retweets (Gross, 2018).

This research aims to produce valid and reliable data and create a clear overview of the salmon aquaculture industry and sentiment among stakeholder groups. In addition, research should further facilitate a complete and robust analysis of the salmon aquaculture industry. Further data and information should be available for other aspects of the salmon farming industry.

API

Twitter's API, https://dev.twitter.com/overview/api, is a separate platform for developers separate from the main website, twitter.com, that is accessible to those wishing to use it (Ignatow & Mihalcea 2019; Kirellii & Arslankaya, 2020). The platform sends the JSON response value. This response value consists of the tweet object, the user's information, the text of the tweet and the upload date and location data (Kirelli & Arslankaya, 2020). Twitter's API had tweet locations, but due to security issues and complaints from users since 2012, it no longer does this, meaning that geographical location is no longer available (Hridoy, 2015). Instead, there are location details the Tweet authors can have in their user profiles or location through indirect location references (i.e., today @UOttawa) (Daume, 2016). Twitter's API defines the data structure it can scrape (Ignatow & Mihalcea, 2019). APIs can hinder data access because of proprietary constraints, data sharing restrictions, firewalls, and even limited replicability (Járic et al., 2020). Other common instances that may disrupt research include adjustments to APIs, and changes to data indexing and preprocessing procedures (Correia et al., 2021).

Web Scraping and Crawling

Web crawling identifies inclusive web pages in a collection through link navigation; scraping refers to extracting the text from web pages (Ignatow & Mihalcea, 2019). Raw data is scrapable directly from the web page. Sites will often have this information in their Terms of Service and the robots.txt file or API. There may be certain limits to crawling and scraping. For example, Twitter's API limits the collection of tweets to ~3200 as to not overwhelm their servers with requests. Usually, rather than storing the entire webpage, web scrapers will only extract and store the content that is requested (Ignatow & Mihalcea, 2019). Scrapers often use programming languages like Python, Java, or Perl to write "from scratch" programs for existing APIs (Ignatow & Mihalcea, 2019).

VADER

A few different lexicons and programs help determine sentiment. Such programs are OpinionFinder, The General Inquirer, SentiWord, RSentiment, NLTK and LingPipe (Anwar Hridoy et al., 2015; Ignatow & Mihalcea, 2018; Öztürk, 2018). However, the most useful for Twitter and social media analysis is VADER. VADER is a lexicon from 2014 that is specifically helpful for polarity detection (positive/negative) and intensity (or strength) of emotion (Hutto & Gilbert, 2014; Mustaqim et al., 2020). It automatically labels and groups data into neutral, negative, or positive categories (Mustaqim et al., 2020). Figure 9 shows the steps that occur before and after the VADER analysis to parse Twitter data.

VADER is open-sourced code that can run in Python under the MIT License (Hutto & Gilbert, 2014). VADER analysis works best on short documents like tweets and sentences rather than large documents, which makes it the perfect tool for analyzing tweets from Twitter. VADER maps lexical features to emotion intensities (sentiment scores) (Singh, 2021). The sentiment score is calculable through a compound score (the sum of positive, negative, and neutral words within a text string). Then it is normalized between -1 (most extreme negative) and +1 (most extreme positive) (Singh, 2021). Thus, the text is more positive if the compound score value is closer to +1 (Singh, 2021).

VADER is the method of choice for this study because it does not require any training data and it works with multiple domains (Singh, 2021). Unlike a machine learning approach where the program is trained on examples and specific lexicons, VADER is a straight out-of-the-box approach to sentiment analysis. VADER efficiently understands the sentiment of text that contains emoticons, slang, conjunctions, and punctuation, which makes it an excellent tool for social media analysis (Singh, 2021).

In Hutto and Gilbert's research (2014), when comparing the correlation coefficient between VADER and individual human raters, VADER (r=0.881) outperforms the human raters (r=0.888).

VADER even exceeds human raters at "correctly classifying the sentiment of tweets into positive, neutral, or negative classes" by 0.96 to 0.84 (Hutto & Gilbert, 2014). Like the Linguistic Inquiry and Word Count (LIWC, or "Luke"), the VADER sentiment lexicon "is gold-standard quality and has been proven by humans" (Hutto & Gilbert, 2014). VADER is especially useful for content in the social media domain, as sites like Twitter can pose severe challenges to the practical application of sentiment analysis (Hutto & Gilbert, 2014). Some of the challenges are the sheer amount of user-generated data that a site like Twitter can produce daily. The context of tweets can also be hard to parse or understand due to the shortness of the text and the use of abbreviations and emojis to express sentiments (Hutto & Gilbert, 2014).

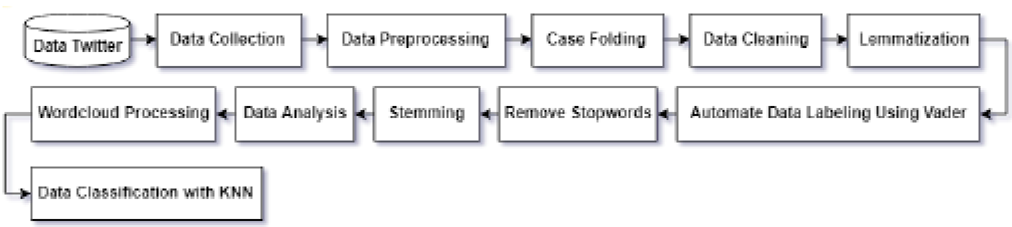

Figure 9. Process for research procedure using Twitter data (Mustaqim et al., 2020)

Query - Collecting the Raw Data

Twint downloads all potentially relevant tweets from Twitter (Öztürk & Ayvaz, 2018). The Twitter search query runs data collection between 08/29/21 and 08/31/21. I saved these tweets in individual CSV files by year and then uploaded them to Google Drive. For Twitter data collection, it is necessary to create a query. It is possible to include several parameters within the question (Anwar Hridoy et al., 2015). Once the construction of the question is complete, the API or the Twint tool runs the data (Anwar Hridoy et al., 2015). The query command for the data is in Appendix B.

Bios Script to Combine with the Raw Data

Since the tweets query runs initially without the bios of individual users, it is necessary to return to Twint and edit some of the code to match up bios with users. This step compares a list of individual usernames from the original CSVs and cross-references the list with the Twint code. The code runs using Python 3.8.9. In addition, it is necessary to modify the original Twint code to fix some errors when trying to scrape the Twitter users' bios. The new regulation runs on top of the original Twint code in the file "*lookup_bios.py"* in Appendix D.

Pandas

After completing the data gathering, it is necessary to clean it up and process it within a data analysis tool like Pandas. Pandas is an open-source Python package that provides fast and easy-to-use data analysis tools. It efficiently implements a data frame (NumFOCUS, 2022). The package NumPy, which also includes support for multi-dimensional arrays (data frames), is used internally by Pandas (NumFOCUS, 2022). Pandas is helpful in this thesis as it allows easy data analysis and manipulation, and it works well within the Google Colaboratory (Google Colab) space. Colab has Pandas preinstalled, so it is simply a matter of importing it and using it.

Google Colaboratory

After collecting the raw data, it is necessary to clean up some errant code and other tags within the CSV files and make sure they are readable and accessible in Excel and Google sheets. Google Colab writes and executes arbitrary Python code through the browser. Google Colab is a free Jupyter notebook environment that runs entirely in the cloud and is especially useful for machine learning and data analysis.

The first step in Google Colab is to set up and import necessary packages. Figure C1 (Appendix C) shows the CSVs in Google Colab. The second step in using Google Colab is used to mount a Google Drive to read the Twitter CSV files. Executing the code from Figure C2 (Appendix C) gives the notebook authorization to connect with the user's Google Drive. This allows the notebook to access the 2006 to 2021 Twitter CSVs and the Bio CSVs that match with Twitter users from Figure C3 (Appendix C).

The next step in the process is to clean up the data. Since the query pulls a lot of information, it is necessary to sort and filter to determine which data columns are required and which are not needed. The columns I kept are ID, name, username, bio, URL, tweets, following, followers, likes, verification, and private. All columns are convertible to their proper *dtypes*.

Figure C4 (Appendix C) shows the Python code for cleaning up each CSV. The basic process for each year is to read the raw data CSV, skipping any metadata, and finally write to a clean data CSV. The data is in CSV files per year from 2006 to 2021. For each year, the code can call the function '*clean_data_for_year*'. Next, the CSV file for that year's raw data is openable from Google Drive and another file to hold the clean return data using python's '*open'* function.

Finally, python's native CSV module reads and writes from these files. The first step is to write the headers into the return file as they are sometimes not in the original CSV. Then, the following steps take place for each row in the original CSV. First, if the row is the CSV header, skip it since the headers are in the previous step. Next, skip it if the row appears to be Twint's metadata. These rows contain "-1" or those that start with "scroll:" and then a random string of characters. Otherwise, write that row to the return CSV. This process ensures that the CSV files have been cleaned-up and are readable.

I then combine the two separate CSV files as there is one file with all the original tweet data and one file with the biographies of the Twitter users from the original file. Then I use the '*combined'* function in Figure C5 (Appendix C). Afterwards, it was necessary to do some tidying of the code as there were discrepancies between the two different CSV files (Figure C6, Appendix C). There were discrepancies due to Twitter's search functionality which pulls tweets where the username or a mention may have the word "aquaculture" even though these tweets have nothing to do with the topic. This step also filters out tweets from users that Twitter may have banned or suspended. Thus, their tweets were temporarily unavailable, even though they may have had a tweet relating to salmon aquaculture. These tweets can be excluded, as there are relatively few cases, and they are unlikely to affect the overall dataset.

Then there are the cases where a bio did not match the account. These were only 1.21% of rows without a bio, which is few enough cases to remove. See this complete step in Figure C7 (Appendix C). Then I rearrange the columns and data to be readable when I download them to an Excel CSV for further data manipulation (Figure C8, Appendix C). I then need to collapse the categories of stakeholders from the Bios code to simplify the data manipulation (Figure C9, Appendix C). Rather than have Columns A-H with either TRUE or FALSE in the cell to determine which category of stakeholder each user is in, I organize them into a single column.

Filtering tweets

Once the steps of collecting, importing, and cleaning up the Twitter data were complete, they needed further processing before use. Due to the casual and random nature of tweeting, the data needs further processing to remove unnecessary information (Anwar Hridoy et al., 2015; Öztürk & Ayvaz, 2018). Each tweet contains metadata information like the user's name (their @), the tweet text, a timestamp for the data or creation, tweet ID, if it is a retweet, and so on (Correia et al., 2021). Twitter does not provide gender as a query parameter, so it is not possible to obtain the gender of a user from their tweets (Anwar Hridoy et al., 2015). Typically, the most relevant information for research would be the tweet itself and the date/time of the tweet and any geotagging or location options if they are available (Daume, 2016). It would be necessary to clean up the data by filtering out duplicate tweets, those with incorrect links or missing information (Daume, 2016), (Edwards et al., 2021).

It is necessary to process the dataset by removing useless words and characters such as “RT” and “@,” converting uppercase letters into lowercase letters, and removing punctuation and numbers so that only text is analyzable (Öztürk & Ayvaz, 2018), (Mustaqim, 2020). I do not keep retweets in the dataset as they do not reflect a new opinion (Öztürk & Ayvaz, 2018). Removal of Emoji characters is also a part of the data cleanup. Emojis impact the overall sentiment; however, they are not a significant focus of research within lexicon models (Öztürk & Ayvaz, 2018). This research also needs to focus on English tweets only as the study focuses on Canada, where one of the primary languages is English.

Remove numbers	Deleting numerical expressions in the texts
Remove punctuations	Deleting special characters and punctuation marks in the texts
Remove stop words	Removal of stop words that do not change the meaning of the sentence specified for Turkish
Remove whitespace	Deleting the blank characters in the text
Word stemming	Determining the word roots using Zemberek Turkish NLP in the sentence [29]

Figure 10. Data preprocessing steps (Kirelli & Arslankaya, 2020)

After the cleaning and filtering, 98.09% of rows remain, meaning that 1.91% of rows no longer contain the word aquaculture (Figure C6, Appendix C). Rows may not include the word 'aquaculture' because they have usernames containing the word 'aquaculture' or mentions and retweets. Again, as the amount of data is low, I remove these rows from the dataset. Then I eliminate those rows without bios. I lose 47,208 rows in this step, which is 8.08% of all rows.

Categorizing Twitter Users by Stakeholder Type

Because the Twitter data is separate from the Twitter user biographies, it is necessary to download and clean up the data to determine which individuals are in which stakeholder groups. This process ends in Google Colab, much like the previous steps.

First, installing and importing the tools necessary to classify and organize the biographies is essential. Figure C10 (Appendix C) shows the tools. Then, I can mount the Google drive to the Colab notebook. See these steps in Figure C12 (Appendix C). Then each string receives a data type, and I add the CSVs into the Colab notebook (Figure C12, Appendix C). I omit the columns with unnecessary data from the dataset in this step. For example, the notebook keeps the following columns: id, name, username, bio, URL, tweets, following, followers, likes, verification, privacy, and location. These columns are helpful in the data analysis, and other columns like tweet id, time zone, mentions and replies I do not keep in the dataset.

I now have 112,029 clean Twitter user bios. I use different categories to group the bios and identify the stakeholder types (Figure C13, Appendix C). These categories are researcher, academic, company, NGO, worker, activist, Indigenous, government, conservationist, fisher, media, water, gamer, tech, prepper, foodie, family, non-ASCII, and non-English. Within these groups, I find keywords by looking through the Excel file of Twitter bios. For example, in the category 'academic,' I see the keywords: researcher, analyst, investigator, scientist, science, scientific, experimenter and fieldwork. The code work at the beginning is to change the text to all lowercase to make it easier to search and replace dashes, quotation marks, and apostrophes. At the end of the chunk of code, the function 'assert' can help to test the code (Figure C13, Appendix C). Test code works by creating test case bios to see if each case catches correctly by the code. For example, one line has the phrase #rod-man to see if the code correctly parses the hashtag and the dash. These just make sure that each grouping works as expected.

The next step involves applying the above functions to the bio (Figure C14, Appendix C). The parts create 19 different stakeholder groups. The code in Figure C15 (Appendix C) determines if the bio does not have a category. It looks over the 19 types, and if the bio does not match any, it goes in the category of 'other.'

Figure C16 (Appendix C) shows the researcher, academic, company, NGO, worker, activist, Indigenous, government, conservationist, fisher, media, water, gamer, tech, prepper, foodie, family, non-ASCII, and non-English categorized into Groups A through H. Groups are necessary because, for example, academics and researchers tend to fall into the same overall category. So, Category A is now researchers and academics; Category B is NGOs, conservationists, and water; Category C is the government, Category D is Indigenous, Category E is media, tech, and gamers; Category F is preppers, foodies, family, non-ASCII and non-English, and Category F is other. In this case, Category F is 'other' because it is all the biographies that could not go into one of the other groups. These are bios where no keyword is present, for example, the bio "looking for peace" or "passionate about knowledge sharing."

The last step is to export the data to a CSV file. The below code in Figure C17 (Appendix C) exports and downloads the file. I can then reupload the file to Google Drive to allow its use in the other Google Colab notebooks. Finally, combining the original Twitter data (with users) to match their bios is necessary. This step allows for easier categorization of the Twitter users by their stakeholder group. I can then do sentiment analysis for stakeholder groups and compare them.

Data Analysis

Once all the above steps are complete, I use the VADER tool to do a sentiment analysis of the individual tweets. The code is below in Figure C18 (Appendix C). This code analyzes each tweet's sentiment (~537,000 tweets) and determines each tweet's overall compound sentiment score. The score can range from -1 to +1, where -1 is negative, +1 is positive, and closer to 0 (or 0) is neutral (Singh, 2021).

Then I download the final CSV file (Figure C19, Appendix C) to aid in the analysis step of the research. This CSV contains the following columns: tweet id, user id, username from a tweet, username from bio, name from tweet, name from bio, tweet, bio, location, language, followers, likes, category, and sentiment.

Canadian Data Subset

It is necessary to gather a subset of data from the overall dataset to analyze the Canadian perspective of sentiment toward aquaculture. The code is in Figure C4 in Appendix C. Within the data from Twitter, there is a location column. As Twitter is very particular about the data they store and track for privacy reasons, the location field in Twitter users' bios is fillable with any data. This means users can say they are from "Toronto, Canada" or from "somewhere over the rainbow", so sorting the data is not easy. The first step is to make sure the location column is all in lowercase so that the code does not need to parse any uppercase letters. The code will also strip any non-letters and split the words upon white spaces.

Because I am looking at Canada, I also need to account for some cities like Montréal and Québec, which use the accented letter 'e', which would be removed if we are only looking at the letters a-z because 'é' is a different Unicode character. Then it is time to create a list of Canadian provinces, territories, and cities for the code to match against the location column of the data. I do this by listing all the province and territory names, their acronyms (i.e., O.N., S.K., B.C., etc.), and then each province or territory's capital city and a few other major cities within those provinces or territories. This creates a subset from the original data of Canadian bios, leaving me with 3,377 tweets, or 1.23% of the data.

FINDINGS

Graphs using the original dataset of 536,988 tweets, include neutral, positive, and negative tweets, show that a significant number of neutral tweets overshadow the data from either positive or negative tweets. An example of a neutral tweet is “In Nanaimo for Aboriginal Aquaculture Association meeting”. The keyword is mentioned; however, it is done so in passing and would receive a neutral score from VADER as it does not lean positively or negatively in terms of sentiment. Rather, it just states a fact or information about the keyword. Therefore, I filter truly neutral tweets (those with a sentiment score of 0), which leaves the dataset with 273,319 unique tweets.

The two main research questions that I address in this thesis are how public sentiment towards salmon aquaculture differs over time and whether public sentiment towards salmon aquaculture differs among stakeholder groups. Findings are in four main categories to address the dependent variable of sentiment and the independent variable of time: overall sentiment, sentiment from year to year (2006-2021), sentiment by stakeholder category and sentiment by stakeholder category per year.

Positive, Negative and Neutral Tweet Examples per Stakeholder

Table 1. Examples of Negative, Neutral and Positive Tweets for each Stakeholder Group

Stakeholder Group	Negative Tweet	Neutral Tweet	Positive Tweet
A. Academic / Researcher	“WWF Sustainable Aquaculture Plans outrages rest of Enviro Community”	“At the Joint Subcommittee on Aquaculture meeting at NOAA”	“Support your urban agriculturist! We here in Milwaukee are proud to boast 2 amazing aquaculture projects.”
B. Industry / Worker	“No sea, no culture, no livelihood for many. RT @MontereyAq: Aquaculture still depends on the sea.”	“Doing a virtual classroom session with my aquaculture online students”	“Cooke aquaculture being honoured at the JA event - a NB success story with 1600 employees!”
C. ENGO / Conservation	“I believe in aquaculture AND food safety. All farmed fish should be tested and disclose feed and finished product contaminants. It matters!”	“All about sustainable aquaculture #permaculture”	“Wonderful meeting at Yale to discuss sustainable aquaculture.”

D. Government	“Belle: Offshore aquaculture is very hostile & expensive to operate. #natlsum11 (It's not being done here yet, w/ exception of test in HI)”	“Aquaculture is world’s fastest-growing source of animal protein”	“Just discovered innovative and fascinating projects at the Aquaculture Laboratory of the Institut des sciences de la mer de #Rimouski.”
E. Indigenous	“Yes even #aquaculture companies must respect #FPIC #UNDRIP & respect Indigenous law when operating in unceded territories.”	“In Nanaimo for Aboriginal Aquaculture Association meeting”	“Good informational day here in Nanaimo... #firstnations sure have #naturalresources & #tradishknowledge in aquaculture... #NAFF”
F. Media	“Here's what's wrong with aquaculture - http://fwix.com/article/62_c1266f3120”	“Ottawa working with B.C. to manage aquaculture: fisheries minister”	“ The worldwide assessment concluded the environmental impact of aquaculture is lower than raising cattle, pigs or poultry”
G. Other	“so, how's your aquaculture industry keeping it's head above water? Canada's is sinking and the salmon is stinking - sad really”	“II am now reading about offshore aquaculture on Wikipedia.”	“Aquaculture is the alternative.”
H. No Category	“Would you like Creutzfeldt Jakob disease (BSE) with your #fish from #aquaculture? Ask your supplier.”	“fleshing out some urban aquaculture concepts.”	“This is the future: Skuna Bay, a fish farm that produces some of the world's best salmon. #sustainability #aquaculture”

Overall Sentiment

Overall Sentiment Analysis of Data

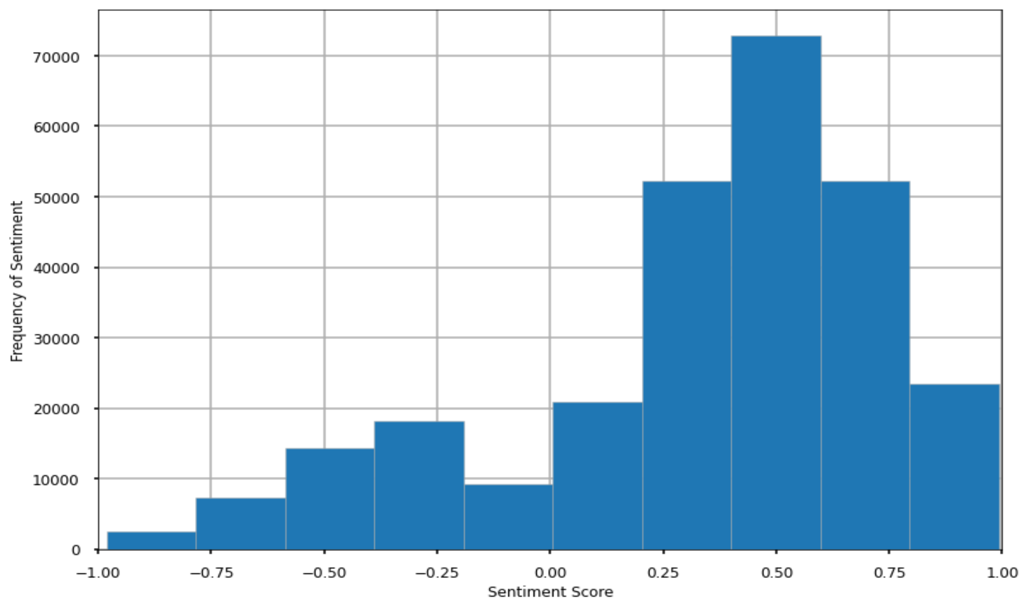

Figure 11. Overall sentiment score of datasets (N=273,319)

Table 2. Mean, median, standard deviation and skewness of dataset (N=273,319)

N	Mean	Median	Standard Deviation	Skewness
273,319	0.329	0.402	0.409	-0.994

Table 2 highlights the mean, median, standard deviation, and skewness of the overall dataset, where N=273,319. The mean is 0.3, the median is 0.4, and the standard deviation is 0.4. A standard deviation of 0.4 shows that the dataset values are relatively consistent and cluster close to the mean. A mean of 0.3 and a median of 0.4 show the data is symmetric as the values are pretty like one another.

A skewness value closer to zero shows a perfectly symmetrical data distribution. A normal distribution, or a "bell curve", exhibits zero skewness. Skewness in the statistical sense measures the symmetry (or asymmetry) of the data distribution. If data has a positive skewness, it means the data is more to the right side of the graph, whereas if data has a negative skewness, it is more on the left side of the graph. Figure 11 shows the overall data plots on a histogram. Table 2 shows a skewness value of -0.994 for the overall dataset. The graph has a moderate negative skew since -0.99 is between -1 and -0.5.

Sentiment Analysis from Year to Year

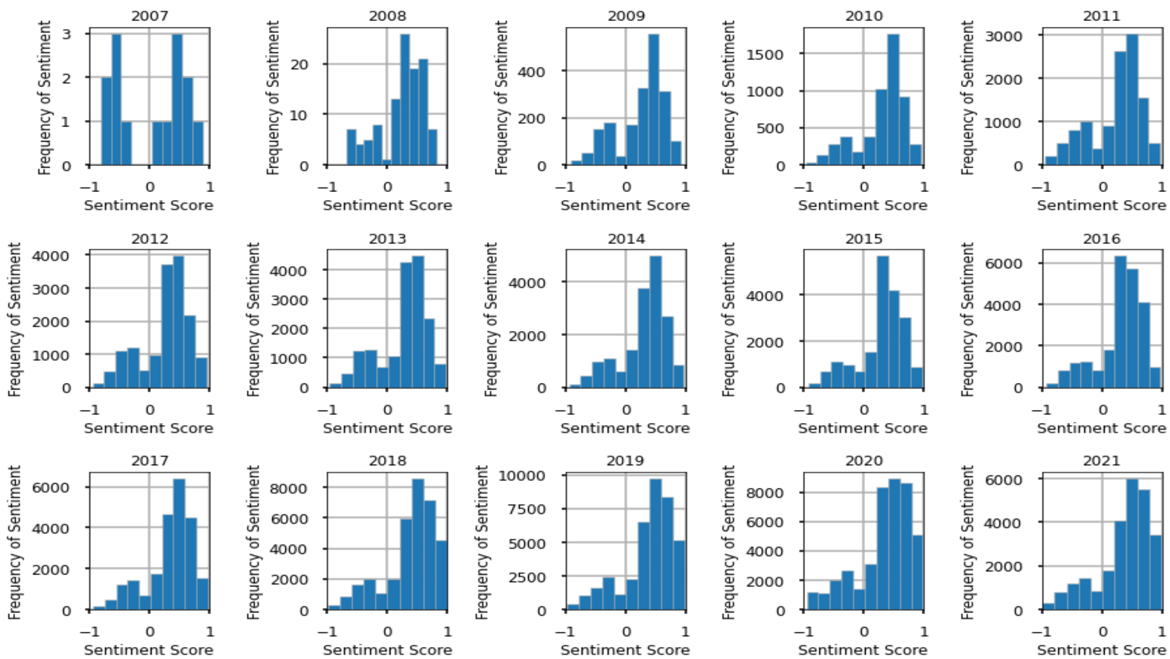

Figure 12. Sentiment score from year to year (2007 to 2021)

Figure 12 is a compilation of histograms from 2007 to 2021, which show the frequency of sentiment across each year. If I exclude 2007, the data skews right, and the peaks tend to fall on the positive sentiment score side (between 0 and 1). A positive graph with peaks is in line with Figure 11 as it also seems to skew left and show a more positive overall sentiment. Figure 13 also shows this trend as the line of best-fit trends upwards, and the points also seem to follow the trendline.

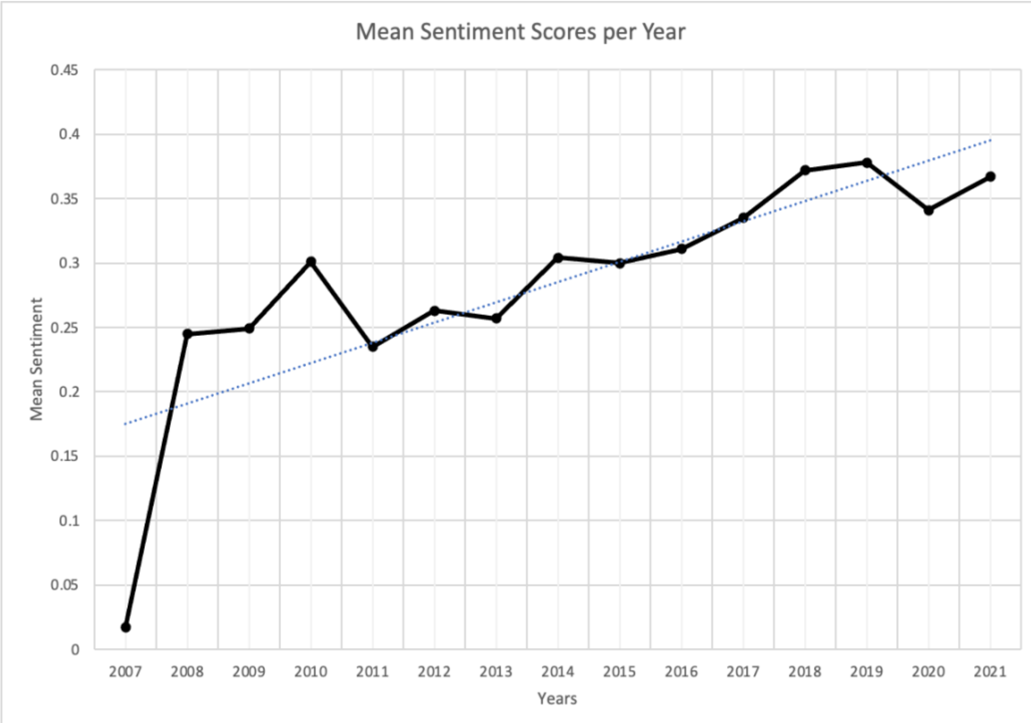

Figure 13. Mean sentiment scores per year

Figure 13 shows the mean sentiment scores per year from 2007 to 2021. The equation for the line of best fit for the graph is y=0.0157x + 0.1595, and the R-squared value is 0.635. When looking at Table 3 below, I can see that the year 2007 only has N=14 data points. The graph also reflects this as 2007 seems to be an outlier compared to the other years. Suppose I remove 2007, the R-squared value changes to 0.7898 (Figure 14). In the social sciences, Chin (1998) and Hair et al. (2011) interpret R-squared values as follows:

- If R-squared is less than 0.19, it is a very weak model.
- If R-squared is between 0.19 and less than 0.25, it is a quite weak model.
- If R-squared is between 0.25 and less than 0.33, it is a weak model.
- If R-squared is between 0.33 and less than 0.50, it is a weak-moderate model.
- If R-squared is between 0.50 and less than 0.67, it is a moderate model.
- If R-squared is between 0.67 and less than 0.75, it is a moderate-strong model.
- If R-squared is equal to or greater than 0.75, it is an absolute strong model.

The R-squared value is a statistical "measure of fit". It indicates how much variation of the dependent variable (in our case sentiment) is explainable by the independent model (in our case time) in a regression model. In social sciences, the smaller the value, the weaker the model, and the larger the number, the stronger the model. In the case of the data in Figure 13, if the dependent variable of sentiment and the independent variable of time is used, an R-squared value of 0.64 shows a moderate model and an R-squared of 0.79 (accounting for the removal of the outlier year 2007) shows an absolute strong model. What this shows is that an increase in positive sentiment from 2007 to 2021 fits the overall line of best fit (or trend line), creating a strong model of the data.

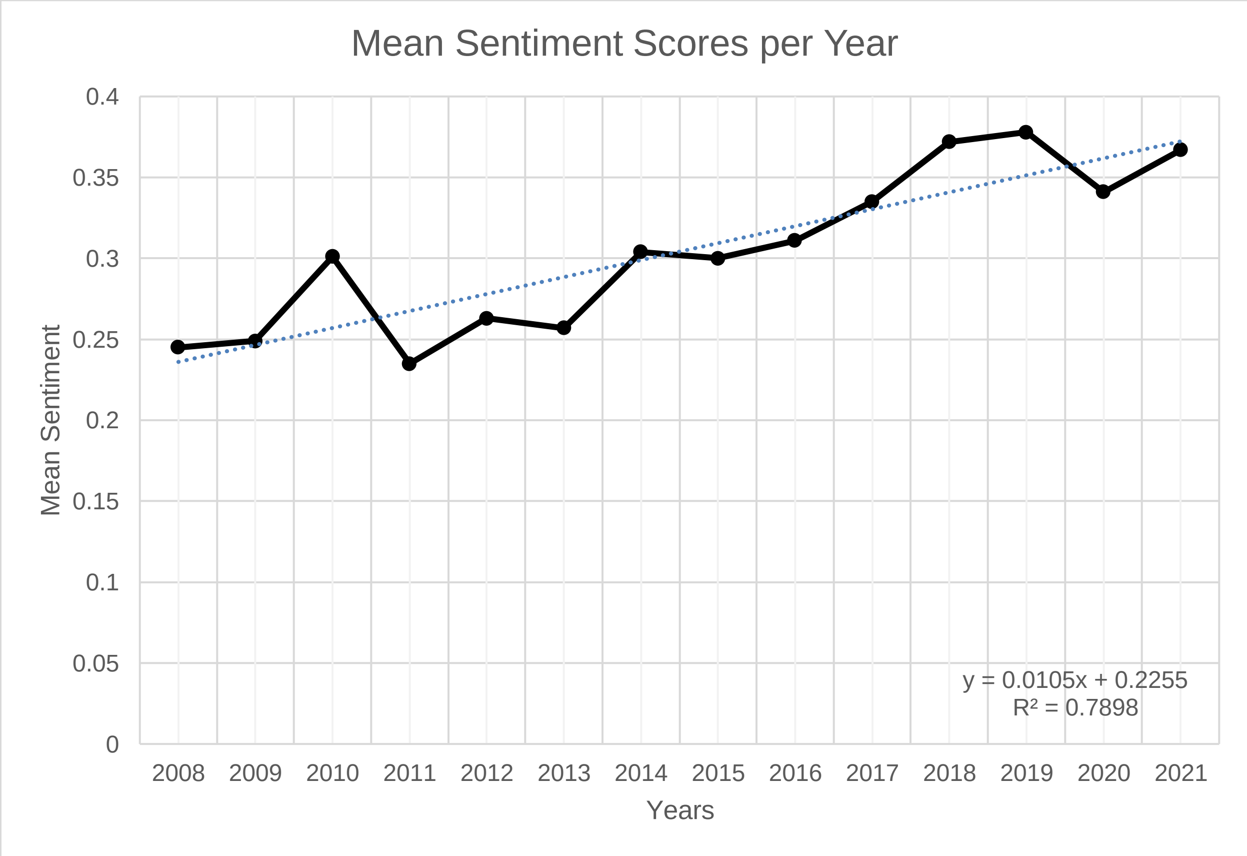

Figure 14. Mean sentiment scores per year (excluding 2007)

Table 3 shows the skewness value for the years 2007 to 2021. Except for 2007, all the years show a moderate negative skew. The year 2007 shows a more normal distribution. However, this could be due to the low sample size (N=14). The year 2007 also has a higher standard deviation than the other 14 years, which means extreme values are more likely, and the data values are dissimilar.

Table 3. Mean, median, standard deviation and skewness of each year from 2007 to 2021*

Year	N	Mean	Median	Standard Deviation	Skewness
2007	14	0.017	0.21	0.612	-0.149
2008	111	0.245	0.34	0.378	-0.943
2009	1,924	0.249	0.382	0.397	-0.818
2010	5,378	0.301	0.402	0.375	-1.027
2011	11,514	0.235	0.361	0.416	-0.824
2012	15,120	0.263	0.382	0.396	-0.874
2013	16,745	0.257	0.361	0.402	-0.86
2014	16,933	0.304	0.402	0.372	-1.018
2015	18,909	0.3	0.382	0.377	-1.062
2016	23,162	0.311	0.402	0.372	-1.114
2017	22,895	0.335	0.402	0.377	-1.053
2018	34,073	0.372	0.445	0.414	-1.066
2019	38,692	0.378	0.459	0.419	-1.082
2020	42,471	0.341	0.44	0.442	-1.015
2021	25,378	0.367	0.457	0.431	-1.046

*Note: There is no data for 2006

Spikes in Sentiment due to Major Events* in the Salmon Aquaculture Industry

*See Appendix A for a complete timeline of the salmon aquaculture industry in Canada. Those bolded events will be the ones that correlate with the years of Twitter data. *

When the events from 2007 to 2021 are looked at, one would expect sentiment to trend downwards (negatively). I expected a downward trend because many of the significant events in the salmon aquaculture industry from 2006 to 2021 were not favourable.

In 2007 (Appendix A), for example, there was a significant court case between the Ahousaht First Nations and Canada (Pinkerton, 2014 pg. 2), as well as a study by Martin Krkosek using 40 years of DFO data that portrays salmon aquaculture very negatively (Macdonald, 2011). In 2008, salmon escaped from a Marine Harvest farm and a farm in Clayoquot Sound which is detrimental to coastal fisheries and the populations that have support from salmon stocks there (Macdonald, 2011). The province of B.C. also put a moratorium on all finfish aquaculture in place during 2008 (Huppert, 2005). In 2009, significant Supreme Court rulings decide that “fish farms are not farms but are fisheries”, and that the Federal Government has exclusive jurisdiction over most salmon aquaculture activities (Flaherty et al., 2019; Huppert, 2005; Pynn, 2009). For many stakeholders like Indigenous groups and researchers, these decisions do not highlight a positive sentiment about the salmon aquaculture industry. 2010 sees the start of the two-year-long Cohen Commission, resulting in 75 recommendations for DFO and groups to improve a bad system (Macdonald, 2011; Viatori, 2019). In 2013 there is a follow-up court case of Ahousaht et al. vs Canada (Pinkerton, 2014 pg. 2). Again, Indigenous sentiment and ENGO and conservationist sentiment are not necessarily very positive as it seems the salmon aquaculture industry is still not heading in a good direction.

The only period(s) that (debatably) have more positive events occurred in more recent years. For example, in 2016 we saw the formation of the Minister of Agriculture’s Advisory Council on Finfish Aquaculture (MAACFA, 2018 pg. 1). In 2020 B.C. announced a further moratorium on the expansion of salmon tenures in the Discovery Islands area to protect critical wild salmon migration routes after hearing messages from several First Nations groups opposing the farms (Flaherty et al., 2019). These are the types of events that one might expect to generate positive sentiment instead of events that highlight the detrimental effects of salmon aquaculture.

Sentiment Analysis by Stakeholder Category

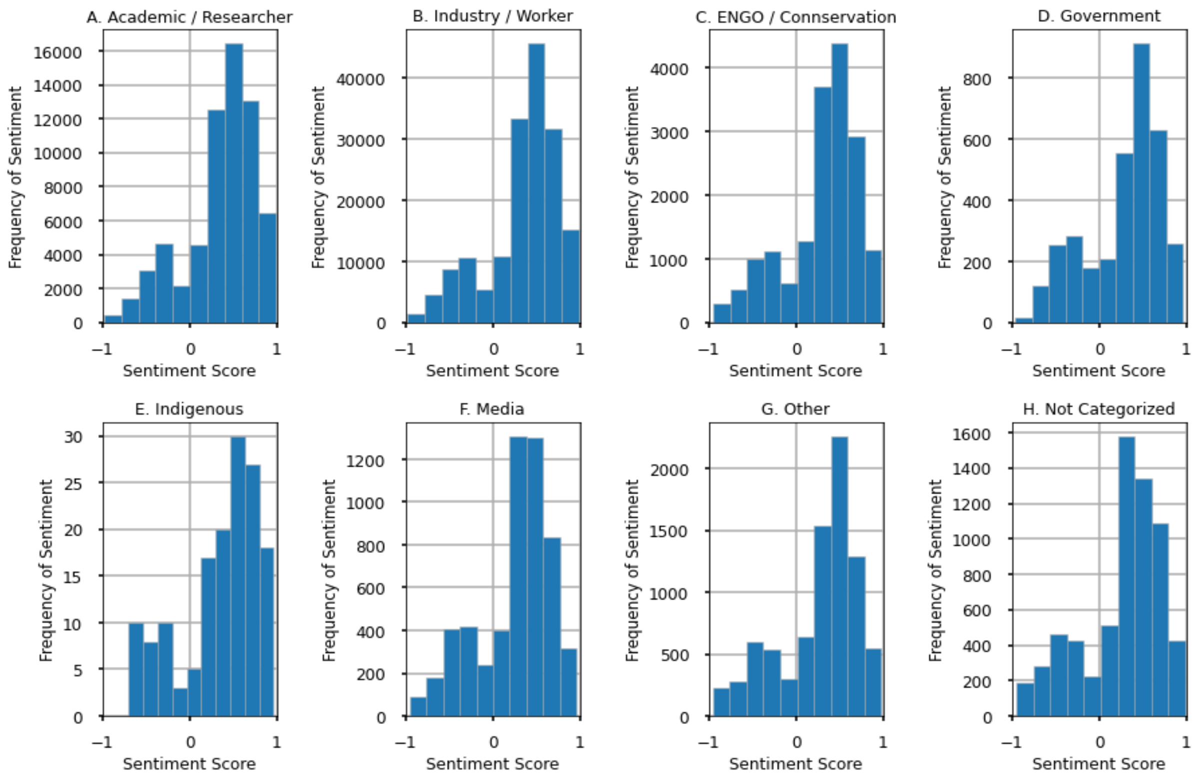

Figure 15. Overall sentiment of each stakeholder group

All eight stakeholder group categories display a moderately negative skew (Table 4). This means the data tend to cluster on the right (more positive side) of the graphs. Figure 15 highlights the frequency of sentiment for of each of the eight stakeholder groups. Again, comparing the mean and median and the standard deviation data in Table 4, I saw that the data in each dataset is relatively similar and consistent and tends to lean on the positive sentiment side. Figure 15 also shows the tendency to lean more positively as the histograms tend to peak and sit further to the right (or positive) side. The Indigenous stakeholder group has an N of 148, meaning that when a comparison is done between the other seven groups, there is not much data. Basing our comparisons of the mean, median, and standard deviation, it does not seem like the data varies too significantly from the average; however, when looking at Figure G5 the R-squared value is 0.0036, which means that it is a very weak model of the dataset. This weak model is explainable in part since many Indigenous communities may not engage on the topic of salmon aquaculture on social media sites, and their opinions are not as easily shareable as they may be for other stakeholder groups.

Table 4. Mean, median, standard deviation and skewness of each stakeholder group

Stakeholder Group	N	Mean	Median	Standard Deviation	Skewness
A. Academic / Researcher	64,859	0.349	0.421	0.403	-0.986
B. Industry / Worker	167,695	0.335	0.42	0.407	-1.02
C. ENGO / Conservation	16,954	0.293	0.4	0.413	-0.956
D. Government	3,424	0.269	0.382	0.425	-0.76
E. Indigenous	148	0.338	0.477	0.45	-0.846
F. Media	5,492	0.244	0.361	0.414	-0.824
G. Other	8,216	0.262	0.382	0.441	-0.902
H. No Category	6,531	0.257	0.382	0.448	-0.869

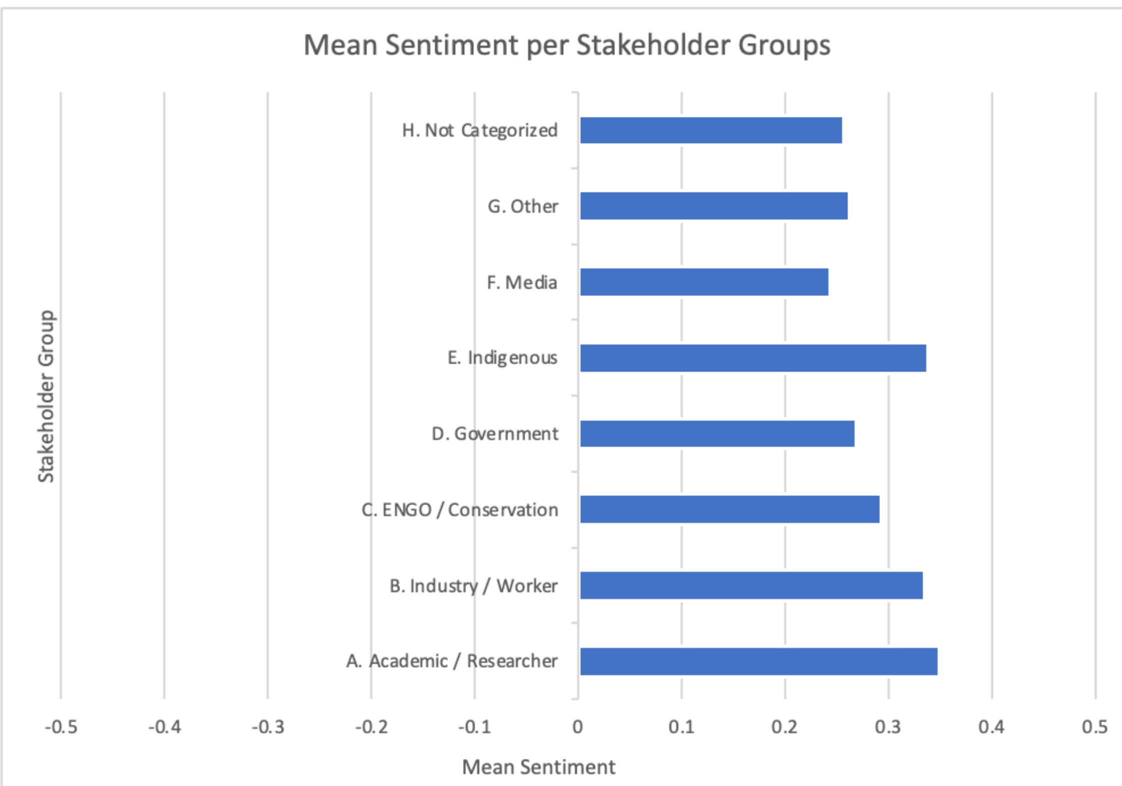

Figure 16. Mean sentiment per stakeholder groups

Sentiment Analysis by Stakeholder Category per Year

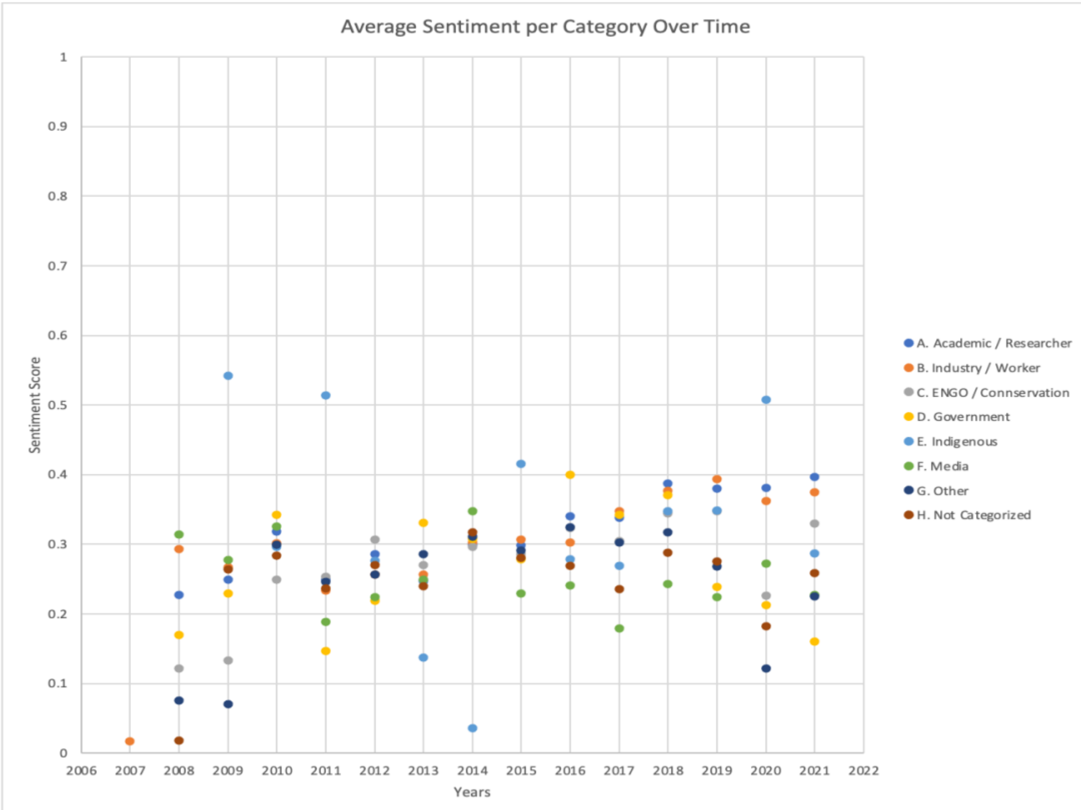

Figure 17. Average sentiment per category over time

Appendix F shows the individual graphs for each stakeholder group and its sentiment over time for a more in-depth Figure 17. The following results are R-squared values of the eight stakeholder groups:

- Academic/Researcher R-squared is 0.8164
- Industry/Worker R-squared is 0.5843
- ENGO/Conservation R-squared is 0.4932
- Government R-squared is 0.0158
- Indigenous R-squared is 0.0036
- Media R-squared is 0.1508
- Other R-squared is 0.1011 OR 0.1462
- No category R-squared is 0.0919

When I remove potential outliers in the categories of Industry/Worker (the year 2007), Other (2008 and 2009) and No Category (2008), I have the following results:

- Industry/Worker R-squared is 0.6745
- Other R-squared is 0.1462
- No Category R-squared is 0.0642

These results fall into categories as follows:

- Academic/Researcher is an absolute strong model
- Industry/Worker R-squared is a moderate model or a moderate-strong model depending on the use of an R-squared value of 0.58 or that of 0.67
- ENGO/Conservation is a weak-moderate model
- Government R-squared is a very weak model
- Indigenous R-squared is a very weak model
- Media R-squared is a very weak model
- Other R-squared is a very weak model regardless of which R-squared value I use
- No Category R-squared is a very weak model regardless of which R-squared value I use

A lesser amount of data can explain the weaker models. Looking at Table G1 (Appendix G), one can see that groups like Academic/Research have thousands of data points for each year (the N column), and a group like Indigenous has less than 50 data points for each year. The Government has only a few hundred in most years, resulting in a weaker R-squared value and model respectively for these categories. Figure 16 shows this same data over time, comparing each of the eight stakeholder groups to one another. In Figure 16, you can see the light blue dots represent the Indigenous stakeholder data, which has more variation from year to year. In contrast, the orange dots representing the Industry/Worker group have less variation from year to year.

Canada

Overall Sentiment Analysis of International & Canada Data

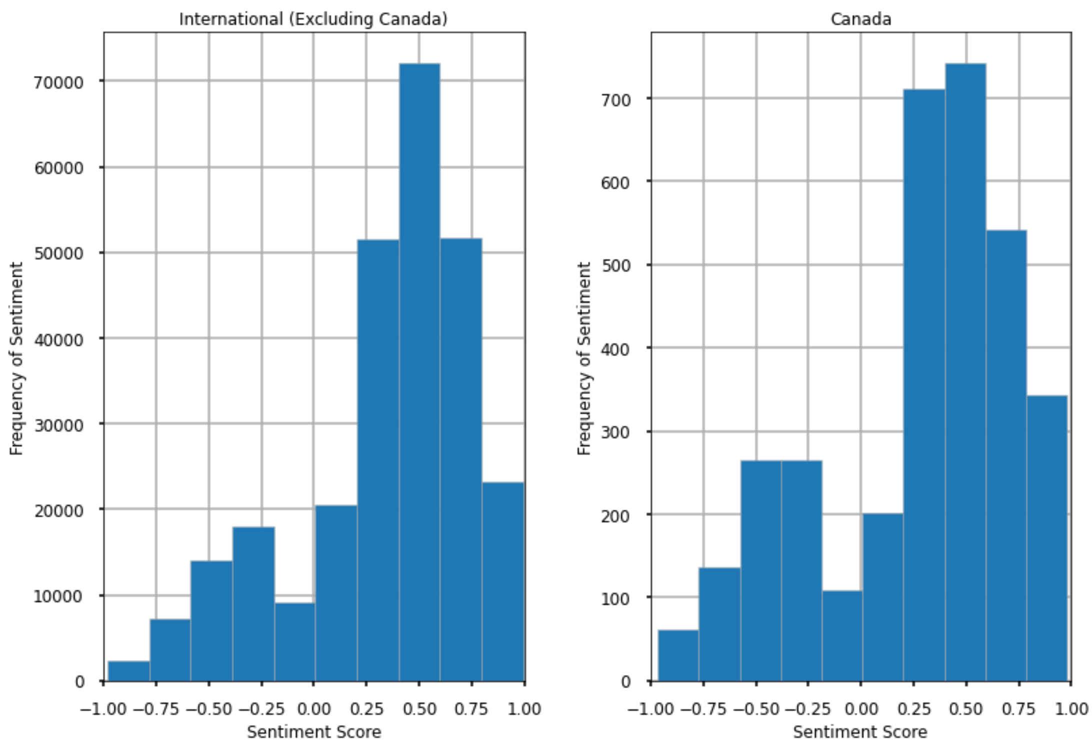

Figure 18. Overall sentiment score of International and Canada datasets (N=273,319)

Table 5. Mean, median, standard deviation and skewness of International and Canada datasets (N=273,319)

Is Canada	N	Mean	Median	Standard Deviation	Skewness
International	269,942	0.33	0.402	0.409	-0.996
Canada	3,377	0.268	0.382	0.458	-0.757

Table 5 highlights the mean, median, standard deviation, and skewness of both the International and Canadian datasets, which are subsets of the overall dataset where N=273,319. Thus, the data available for Canada is 3,377/273,319=0.0123, or 1.23% of the overall dataset. The mean is 0.33, the median is 0.4, and the standard deviation is 0.4 for the International dataset which is very close to the overall dataset values where the mean is 0.3, the median is 0.4, and the standard deviation is 0.4. For the Canadian dataset the mean is 0.27, the median is 0.38, and the standard deviation is 0.46. A standard deviation of 0.4 and 0.46 are very similar and show that the dataset vales are consistent and cluster close to the mean.

Table 5 shows a skewness value of -0.996 for the International dataset and -0.757 for the Canadian dataset. The graph has a moderate negative skew since -0.996 is between -1 and -0.5, as is -0.757.

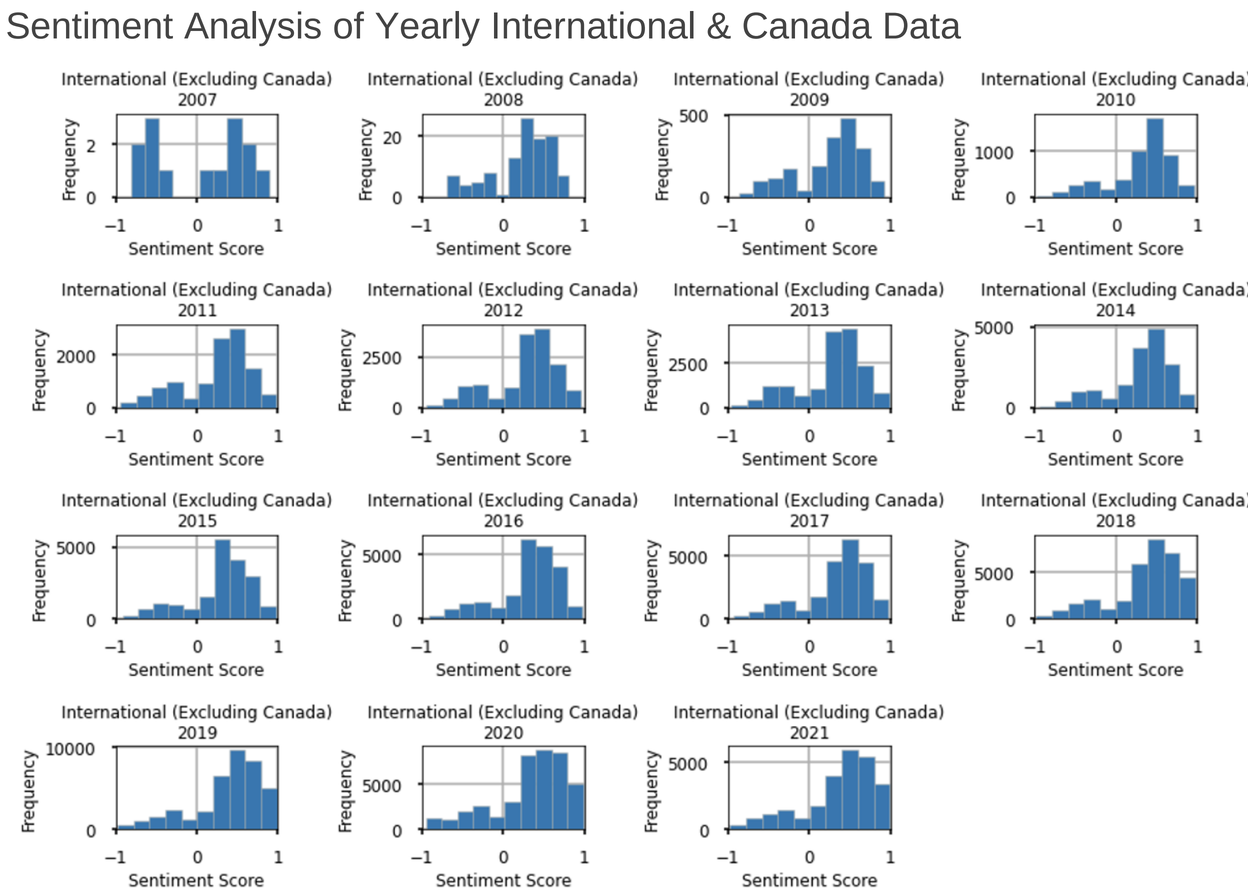

Figure 19. Sentiment score of International dataset from year to year (2007 to 2021)

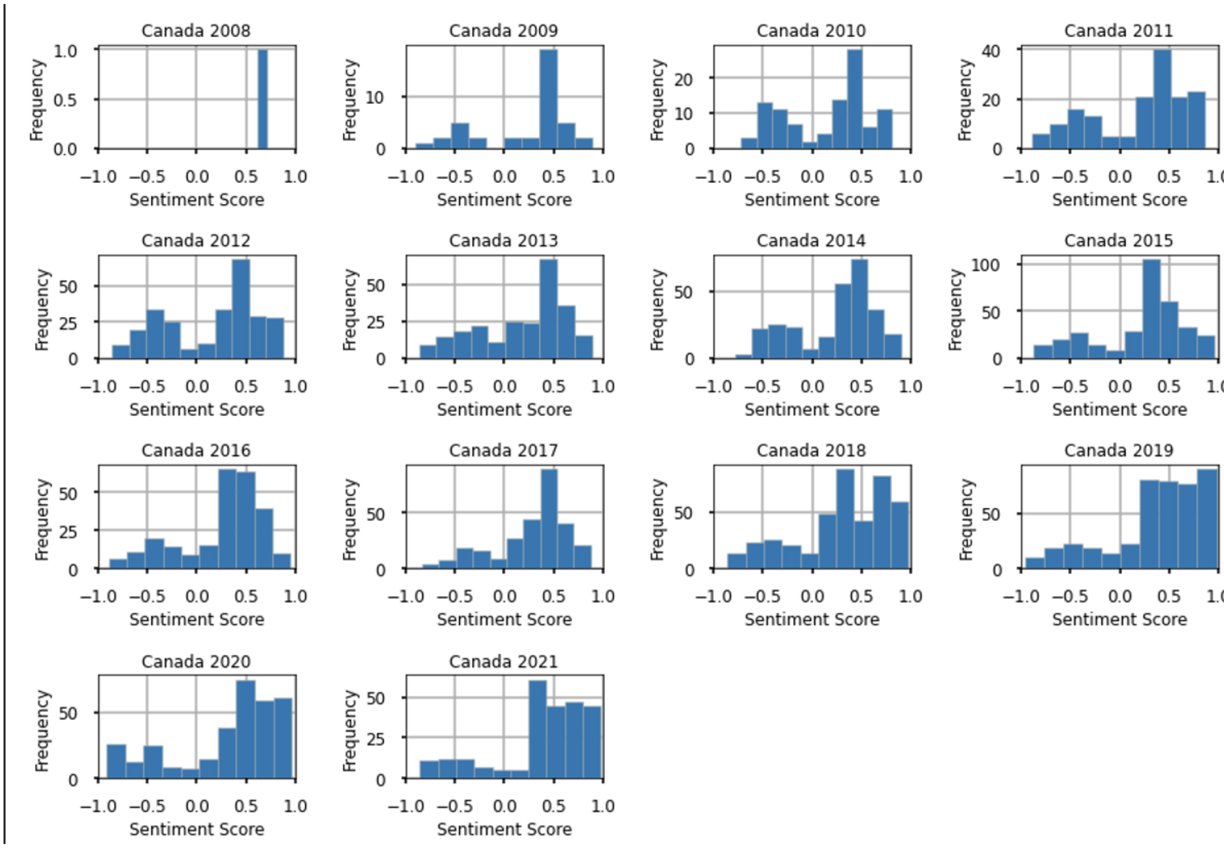

Figure 20. Sentiment score of Canada dataset from year to year (2007 to 2021)

Figures 19 and 20 are a compilation of histograms from 2007/2008 to 2021, which show the frequency of sentiment across each year for both the Canadian and International datasets. If we look at the years from 2009 onward for the International set, most of the data tends to sit toward the right side of the graph (the positive side). For the Canadian data the graphs also trend toward the right side, however, it is not as strong since the graphs have a lot more variation in the peaks and valleys.

Figures 21 and 22 show the mean sentiment scores per year from 2008/2009 to 2021 for both the International and the Canada dataset. If we look at Table 6, we notice that the year 2008 is quite different than the rest of the years. The year 2008 has an N=1 for Canada, and an N=14 for International, whereas the rest of the years have more data points. Thus, we exclude the year 2008 from our dataset (2006 & 2007 were already excluded as they have no data). The equation for the line of best fit for the International graph is y=0.0105x + 0.2263, and the R-squared value is 0.7853. The equation for the line of best fit for the Canada graph is y=0.0182x +0.1221, and the R-squared value is 0.8028.

For the data shown in Figure 21, the R-Squared value of 0.7853 for the International dataset shows an absolute strong model. Figure 22 shows the Canadian dataset, with a value of 0.8028, which is an absolute strong model.

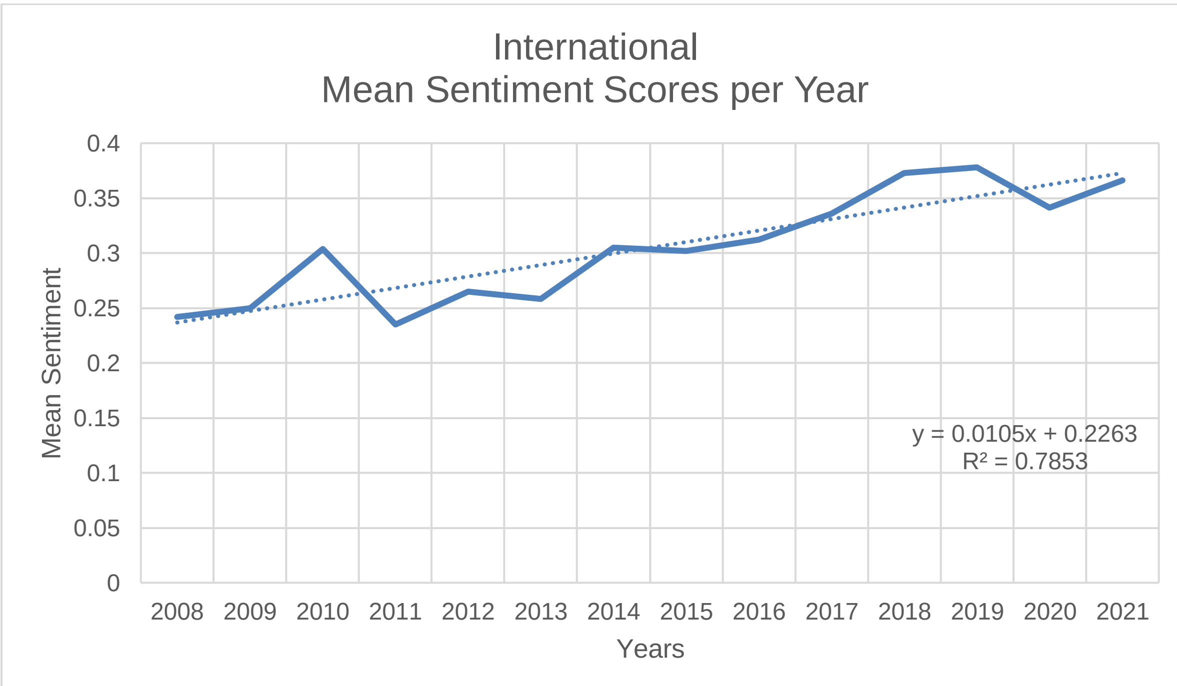

Figure 21. Mean International dataset sentiment scores per year

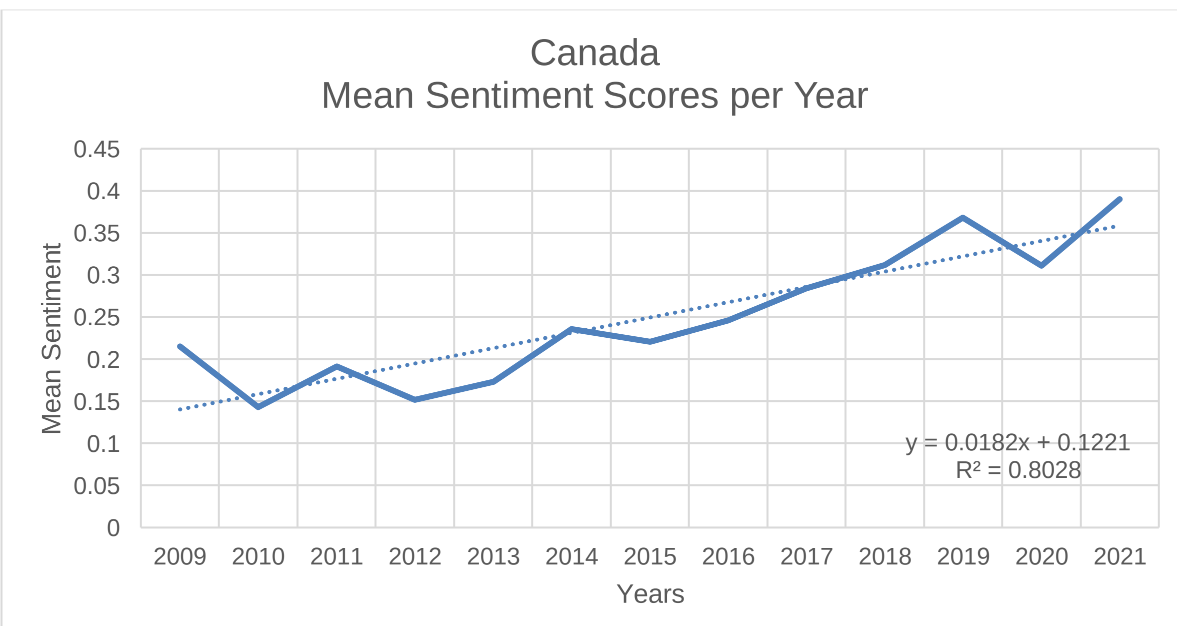

Figure 22. Mean Canada dataset sentiment scores per year

Table 6 shows the skewness value for the years 2007/2008 to 2021. All the values for the both the International and Canadian dataset show a negative skew, which means that the data is typically clustered on the right side of the graph. For the Canadian dataset the year 2008 does not have a standard deviation or skewness value as there is only one datum. The values between -1 and -0.5 have a moderate negative skew, whereas the values between -0.5 and 0.5 have an approximately symmetric distribution. The values that fall beyond -1 have a highly skewed distribution. In the Canadian dataset those years with a value beyond -1 or +1 are 2019 and 2021. In the International dataset those years are 2010, 2014, 2015, 2015, 2017, 2018, 2019, 2020, and 2021.

Table 6. Mean, median, standard deviation and skewness of International and Canada datasets for each year from 2007 to 2021*

Is Canada	Year	N	Mean	Median	Standard Deviation	Skewness
International	2007	14	0.017	0.21	0.612	-0.149
International	2008	110	0.242	0.34	0.378	-0.933
International	2009	1884	0.25	0.382	0.396	-0.814
International	2010	5279	0.304	0.402	0.374	-1.041
International	2011	11354	0.235	0.361	0.415	-0.827
International	2012	14857	0.265	0.382	0.395	-0.882
International	2013	16502	0.258	0.361	0.401	-0.863
International	2014	16652	0.305	0.402	0.372	-1.025
International	2015	18573	0.302	0.382	0.376	-1.065
International	2016	22909	0.312	0.402	0.371	-1.116
International	2017	22619	0.336	0.402	0.377	-1.054
International	2018	33656	0.373	0.455	0.414	-1.071
International	2019	38260	0.378	0.459	0.418	-1.083
International	2020	42145	0.341	0.44	0.441	-1.015
International	2021	25128	0.366	0.457	0.431	-1.046
Canada	2008	1	0.612	0.612	N/A	N/A
Canada	2009	40	0.215	0.382	0.464	-0.904
Canada	2010	99	0.143	0.318	0.431	-0.366
Canada	2011	160	0.191	0.361	0.467	-0.595
Canada	2012	263	0.152	0.318	0.47	-0.413
Canada	2013	243	0.173	0.325	0.446	-0.635
Canada	2014	281	0.236	0.361	0.398	-0.618
Canada	2015	336	0.221	0.318	0.442	-0.831
Canada	2016	253	0.246	0.34	0.414	-0.94
Canada	2017	276	0.284	0.382	0.367	-0.959
Canada	2018	417	0.312	0.382	0.462	-0.706
Canada	2019	432	0.368	0.454	0.476	-1.036
Canada	2020	326	0.311	0.44	0.532	-0.932
Canada	2021	250	0.39	0.477	0.467	-1.084

*Note: There is no data for 2006 in International & 2006 and 2007 in Canada

Sentiment Analysis of International & Canada Data Stakeholder Category

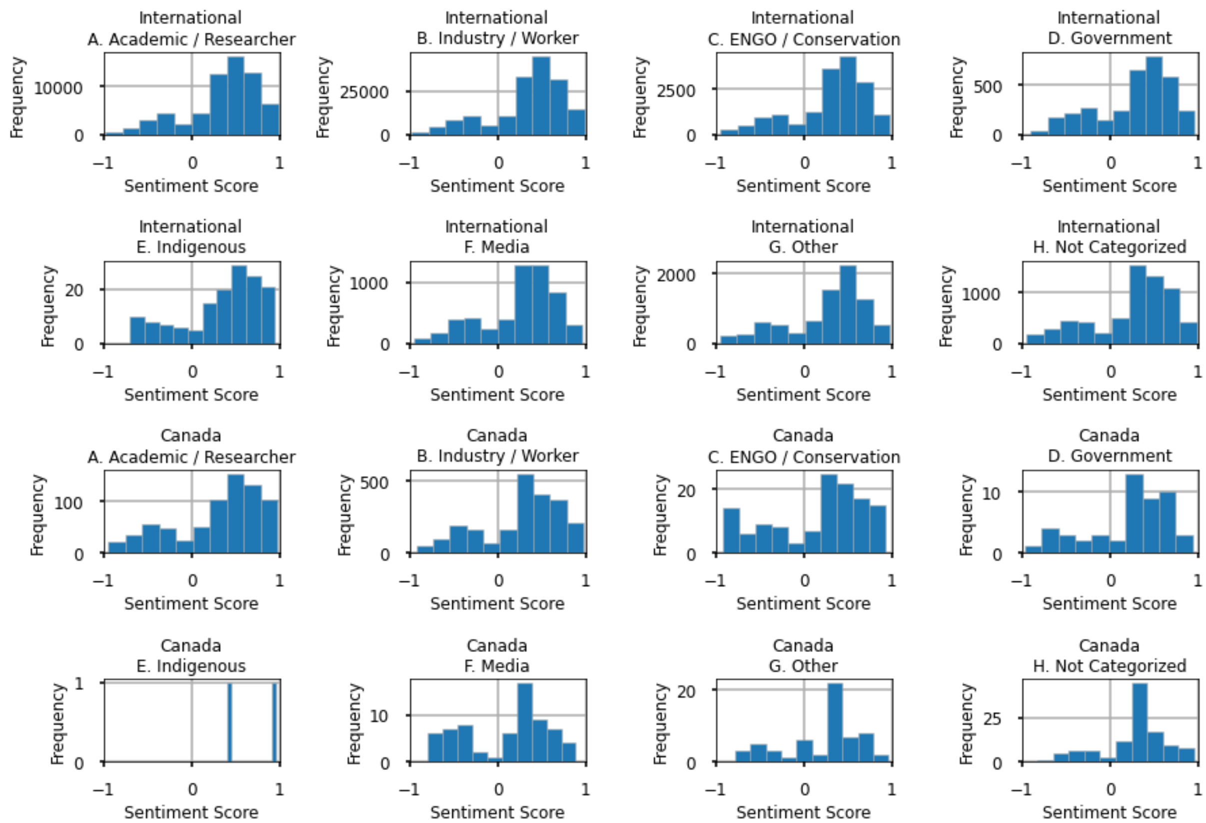

Figure 23. Overall sentiment of each stakeholder group in International and Canada datasets

In the International dataset all eight stakeholder categories display a negative skew (Table 6). The skewness values are all between -1 and -0.5, meaning all 8 graphs have a moderate negative skew as the data tends to be further to the right (the positive side).

In the Canadian dataset the Indigenous group does not have a skewness value as N is too low at N=2 (Table 7). All the values are negative; however, the Media stakeholder group has a skewness value of -0.443 meaning it is closer to an approximately symmetric distribution (Table 7). The findings match with Figure 23 and Figure 24 which show the mean sentiment of each stakeholder group for both the International and Canadian dataset.

Table 7. Mean, median, standard deviation and skewness of International & Canada datasets per stakeholder group

Is Canada	Stakeholder Group	N	Mean	Median	Standard Deviation	Skewness
International	A. Academic / Researcher	64137	0.35	0.421	0.402	-0.987
International	B. Industry / Worker	165455	0.336	0.421	0.406	-1.023
International	C. ENGO / Conservation	16828	0.294	0.4	0.411	-0.956
International	D. Government	3374	0.27	0.382	0.424	-0.757
International	E. Indigenous	146	0.333	0.477	0.45	-0.845
International	F. Media	5425	0.246	0.361	0.413	-0.828
International	G. Other	8157	0.262	0.389	0.441	-0.902
International	H. No Category	6420	0.257	0.382	0.449	-0.867
Canada	A. Academic / Researcher	722	0.295	0.411	0.486	-0.766
Canada	B. Industry / Worker	2240	0.272	0.382	0.447	-0.757
Canada	C. ENGO / Conservation	126	0.147	0.307	0.539	-0.622
Canada	D. Government	50	0.21	0.339	0.466	-0.919
Canada	E. Indigenous	2	0.684	0.684	0.398	N/A
Canada	F. Media	67	0.104	0.318	0.477	-0.443
Canada	G. Other	59	0.237	0.361	0.426	-0.898
Canada	H. No Category	111	0.277	0.318	0.353	-0.927

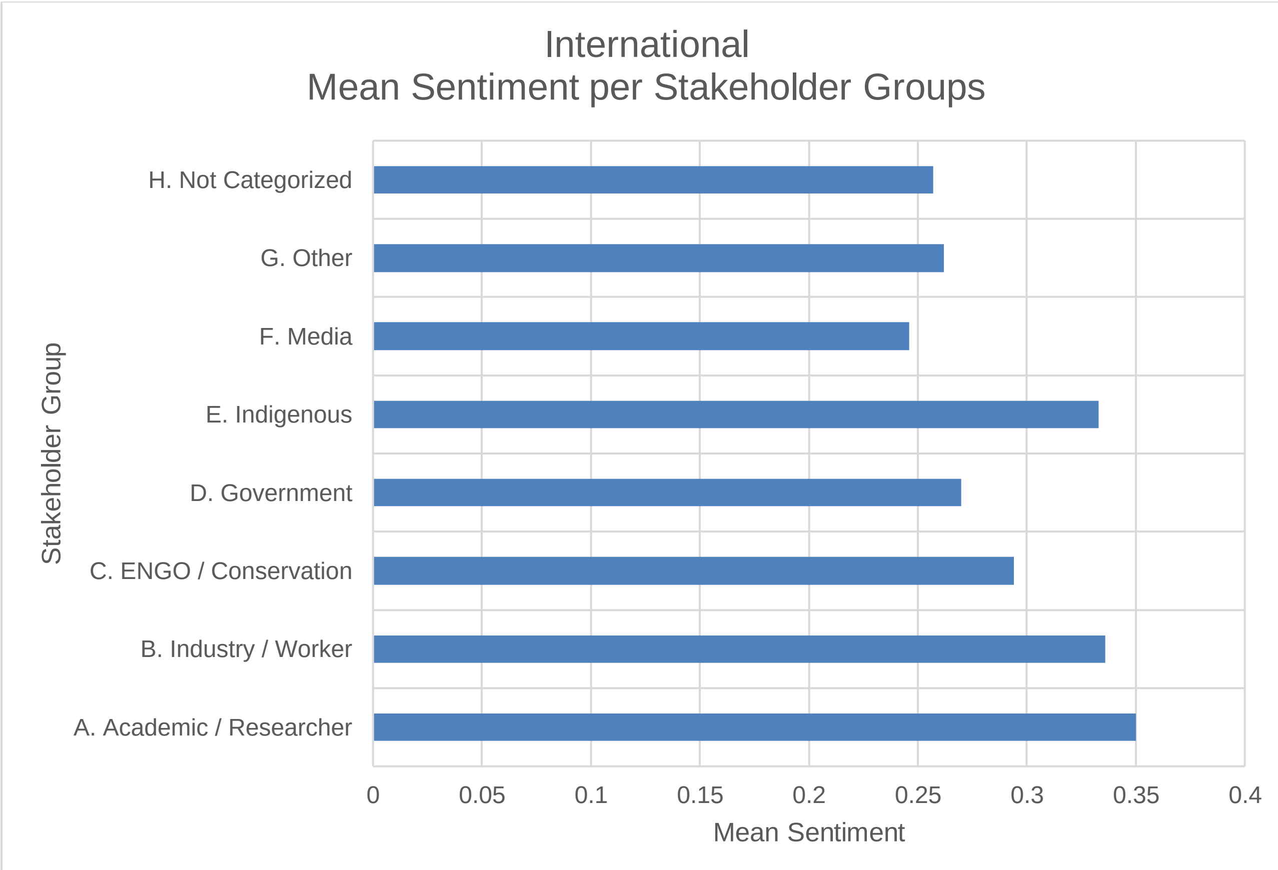

Figure 24. Mean sentiment per stakeholder group for International dataset

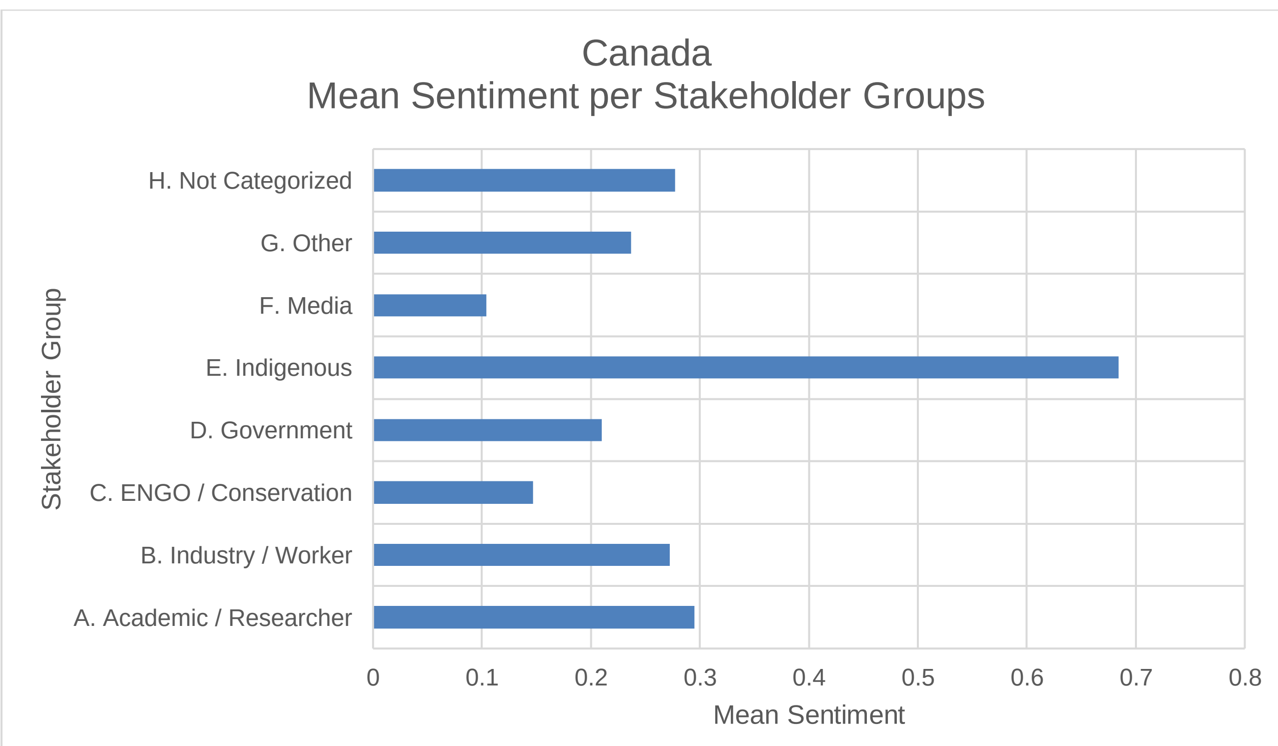

Figure 25. Mean sentiment per stakeholder group for Canada dataset

Sentiment Analysis of International & Canada Data by Stakeholder Category per Year

Table G2 (In Appendix G) shows the skewness value for the years 2007/2008 to 2021. All the values for the International dataset show a negative skew, meaning the data is typically closer to the right side of the graph. For the Canadian dataset the year 2008 does not have a standard deviation or skewness value as there is only one piece of data in that year. The Canadian dataset also contains eleven years that have a positive skewness value meaning that the data will be clustered toward the left side of the graph. These stakeholder groups and years are:

- Academic/Researcher skewness value of 1.385
- ENGO/Conservation skewness value of 0.747
- ENGO/Conservation skewness value of 0.444
- Government skewness value of 0.737
- Media skewness value of 0.663
- Media skewness value of 0.472
- Media skewness value of 0.284
- Media skewness value of 1.794
- Other skewness value of 0.399
- Other skewness value of 0.267
- No Category skewness value of 0.149

Those groups that show an approximately symmetric distribution have values between -0.5 and +0.5. They are:

International

- 2008 ENGO/Conservation group has skewness value of 0.36
- 2021 Government group has skewness value of -0.314
- 2011 Indigenous group has skewness value of -0.32
- 2017 Media group has skewness value of -0.496
- 2008 Other group has skewness value of -0.453
- 2009 Other group has skewness value of -0.294
- 2020 Other group has skewness value of -0.49

Canada

- 2016 Academic group has skewness value of -0.457
- 2010 Industry/Worker group has skewness value of -0.369
- 2012 Industry/Worker group has skewness value of -0.258
- 2020 ENGO/Conservation group has skewness value of +0.444
- 2018 Government group has skewness value of -0.397
- 2020 Government group has skewness value of -0.03
- 2013 Media group has skewness value of -0.472
- 2014 Media group has skewness value of -0.284
- 2013 Other group has skewness value of -0.399
- 2015 Other group has skewness value of +0.267
- 2019 Other group has skewness value of -0.237
- 2012 No Category group has skewness value of -0.324
- 2020 No Category group has skewness value of +0.149

A few notable cases occur in the International and Canada categories where a skewness falls above -2. These are the International Media group in 2008 with a skewness value of -2.46, the Canadian Media group in 2015 with a skewness value of -2.038, and the Canadian No Category group in 2016 with a skewness value of -2.247. These 3 years show a highly skewed distribution in the negative direction in all 3 cases, which means that the data will be far right on the graphs.

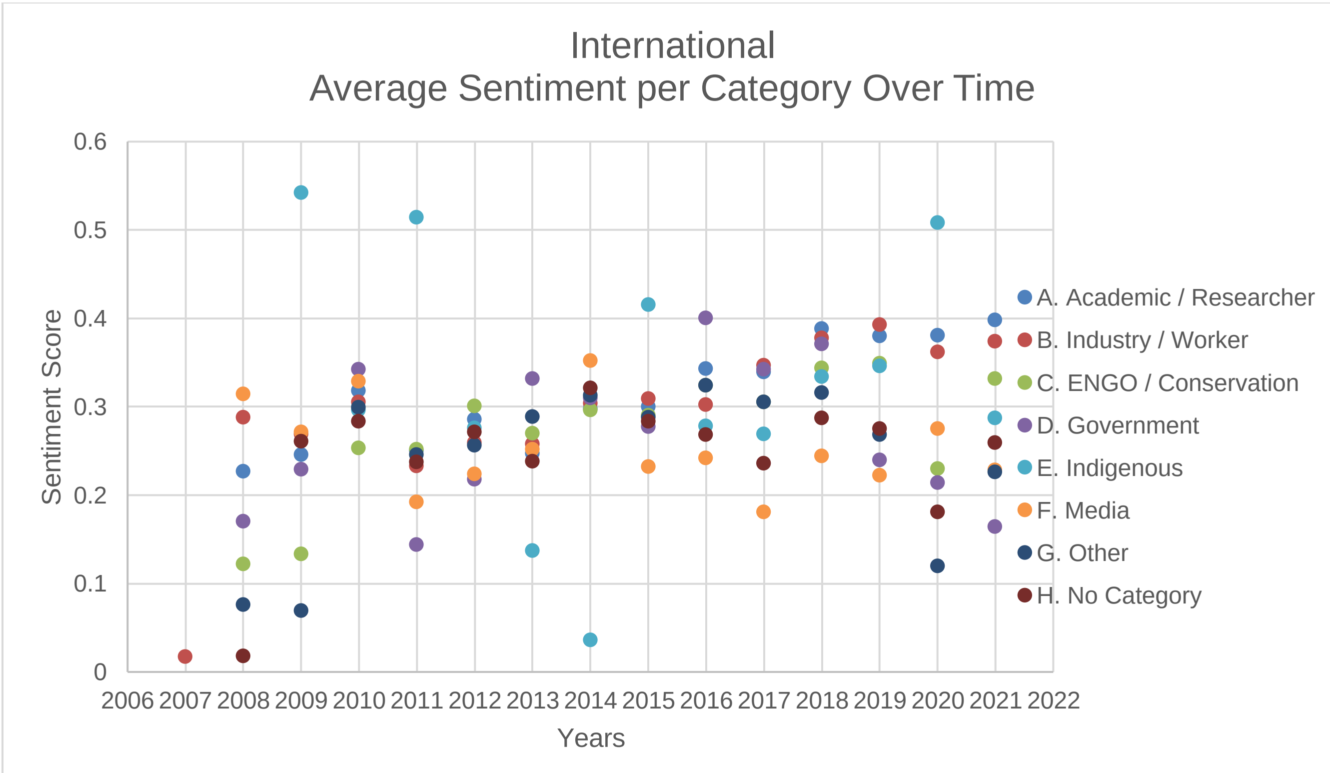

Figure 26. Average sentiment for International dataset per category over time

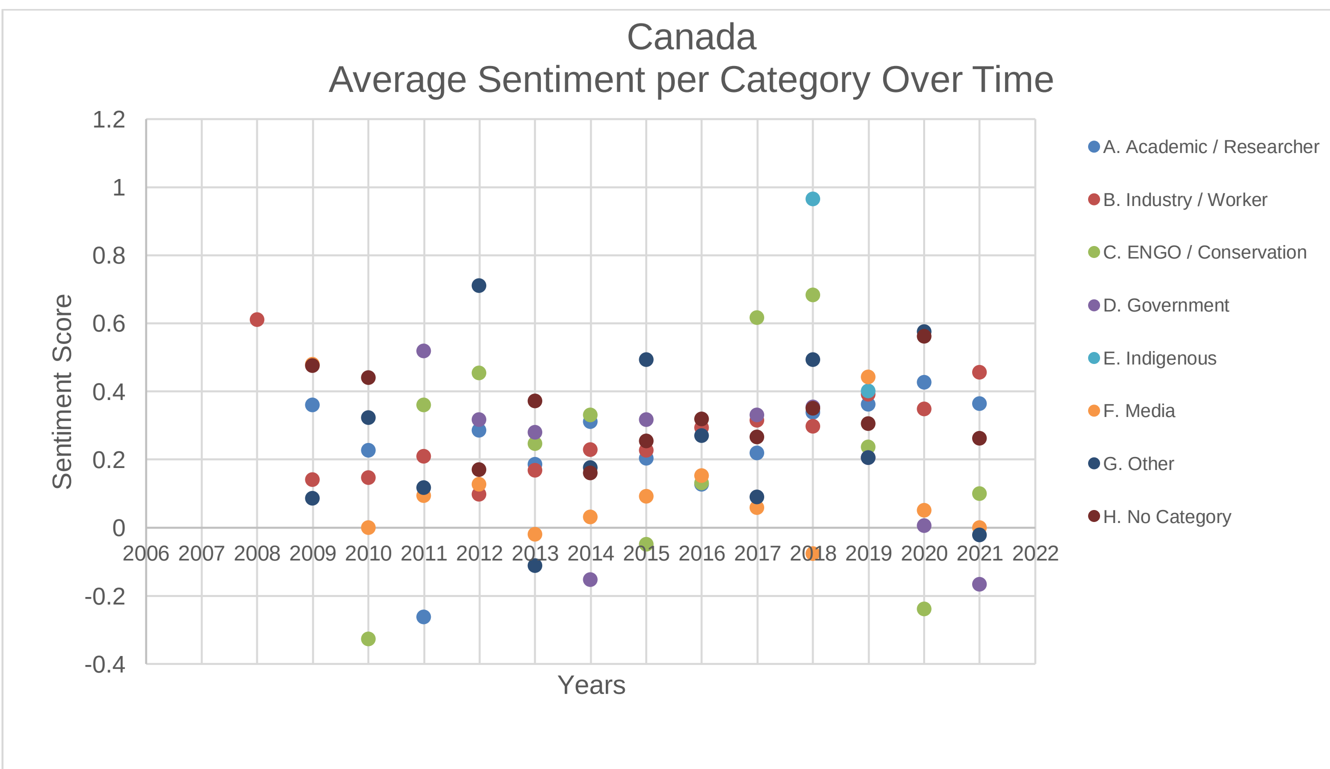

Figure 27. Average sentiment for Canada dataset per category over time

Appendix F shows the individual graphs for each stakeholder group and its sentiment over time for the International and Canadian datasets. They show an in-depth view of what Figure 26 and Figure 27 show. When looking at the R-squared values for the eight Stakeholder categories, I see the following results:

International R-Squared

- Academic/Researcher R-squared is 0.8202, an absolute strong model
- Industry/Worker R-squared is 0.5842, a moderate model
- ENGO/Conservation R-squared is 0.5111, a moderate model
- Government R-squared is 0.0185, a very weak model
- Indigenous R-squared is 0.0046, a very weak model
- Media R-squared is 0.1423, a very weak model
- Other R-squared is 0.0997, a very weak model
- No category R-squared is 0.0926, a very weak model

Canada R-Squared

- Academic/Researcher R-Squared is 0.1907, a quite weak model
- Industry/Worker R-Squared is 0.09, a very weak model
- ENGO/Conservation R-Squared is 0.0016, a very weak model
- Government R-Squared is 0.287, a weak model
- Indigenous has no R-Squared value as there is not enough data to calculate this value
- Media R-Squared is 0.0392, a very weak model
- Other R-Squared is 0.0051, a very weak model
- No Category R-Squared is 0.0027, a very weak model

A lesser amount of data can explain the weaker models. Looking at Table G2 (In Appendix G), one can see that groups like Academic/Research have thousands of data points for each year (the N column), and a group like Indigenous has less than 50 data points for each year (or only 1 to 2 values in the Canadian data subset). Figure 26 and Figure 27 show the data points for each stakeholder group for each of the years in the International and Canadian datasets. The more closely clustered and sparsely spread dots signify that model is a good one, as we see for International Academic/Researcher group. If we look at a group like the ENGO/Conservation group in the Canada dataset we see it has an R-squared value of 0.0016, which shows a very weak model of the data.

RECOMMENDATIONS & DISCUSSION

There are several gaps in our knowledge about salmon aquaculture in Canada and stakeholder management theory that would benefit from further research. Salmon aquaculture is a lucrative business in Canada as well as globally. The aquatic environment covers roughly 72% of Earth's surface, and aquatic species are more at risk than their fellow terrestrial species (Jarić, 2020). While there is much research on the topics within this thesis, it is challenging and time-consuming to conduct high-quality social science research, especially regarding salmon aquaculture and aquatic ecosystems (Jarić, 2020). Therefore, there is an increasing focus on the online mining of data. It is free and usually easy to acquire a source of information and data that can offer much insight to stakeholders. This section discusses the results, the implications and significance of the research, the research limitations, and the recommendations for further research.

Explanation & Interpretation of Results

The sample size of the dataset is 273,319 unique tweets. The Canadian sample size was 3,377 unique tweets. Neutral tweets (those mentioning aquaculture in passing and not highlighting any specific feeling towards the topic) were filtered out to achieve these datasets since they do not aid in the findings to answer the research questions. The two main research questions that I address are how public sentiment towards salmon aquaculture differs over time and whether public sentiment towards salmon aquaculture differs among stakeholder groups.

Findings are broken down into two main groups: the overall dataset and the Canadian data subset. Within these two groups they are broken down into four main categories to address the dependent variable of sentiment and the independent variable of time: overall sentiment, sentiment from year to year (2006-2021), sentiment by stakeholder category and sentiment by stakeholder category per year.

Of the overall dataset where N=273,319 tweets, the mean is 0.3, the median is 0.4, and the standard deviation is 0.4. This data shows that points are relatively consistent and cluster close to the mean, and the data is symmetric. The overall dataset has a skewness value of -0.994 which shows a moderate negative skew since it is between -1 and -0.5. Figure 13 plots the mean sentiment scores for each year. It had an R-squared value of 0.635, and if the outlier data was ignored, an R-squared value of 0.7898. This value indicates an absolute strong model of the data. What this means is that there is an increase in positive sentiment from 2007 to 2021, as the data fits the trend line and shows a strong model. Most of the individual years of data display a moderate negative skew, and again are consistent models of the data, which supports the fact that sentiment does become more positive over time.

The eight stakeholder groups all display a moderate negative skew. Looking at the mean, median and standard deviation we can see that the data is relatively consistent and again, tends to lean toward the positive side overall. The Academic/Researcher and Industry/Worker groups have the strongest models, the ENGO/Conservation has a weak-moderate model and the remaining stakeholder groups have very weak models. For the weaker models, these may come from the fact that they have lower N values. These were also the Other and No Category groups which were not the focus of this research as it could not be determined what kind of a stakeholder these individuals could have been.

When looking at the Canadian subset where N=3,377 (a 1.23% subset of the overall dataset) the mean is 0.27, the median 0.38, the standard deviation 0.46, and there is a skewness value of -0.76. Again, these are good values as the data is consistent and clustered closely around the mean. The Canadian graph has a moderate negative skew, like that of the overall dataset. The Canadian mean sentiment scores per year line graph has an R-squared value of 0.8028 (excluding 2008 as an outlier), which is an absolute strong model. When looking at the Canadian dataset of stakeholders' sentiment across the years, we see there are 11 years with a positive skewness value, which means that the data skews towards the left (negative) side of the graphs. The individual stakeholder groups have quite weak and very weak models, or even a model without enough data to even calculate an R-Squared value. The research would benefit from a deeper look into stakeholder sentiment, especially at a temporal scale to see if there are any periods where a shift might occur from negative to positive.

The data supports the hypothesis that sentiment would increase over time. It also highlights the differences between some stakeholder groups, but I believe further research is needed in this area to support concrete decision-making in the industry.

Implications & Significance of the Research

The findings in this thesis are essential to all stakeholders and the salmon aquaculture industry. In addition, the thesis offers a deeper insight into the opinions and sentiments of different stakeholders and the public about the topic of salmon aquaculture. Stakeholder theory argues that organizations are responsible for many different stakeholders, not just the shareholders. The sentiment analysis results within this thesis show that groups like academics seem to have the strongest sentiment and the most positive-leaning model. However, other groups like the media and government have more variable sentiments and fewer overall data points. If these patterns are understood, firms can better understand and engage with different stakeholders that hold different views about their industry.

The salmon aquaculture industry is complex and changes rapidly. Allowing for further data and insight into the public's sentiment and the industry's stakeholders could allow a firm to be proactive in its decision-making rather than reactive. Using available data allows for real-time insight into the industry and can help influence business decisions and actions and potential policies for government stakeholders. Further social media research will be helpful in this field and gather unbiased information and opinions of the public. Understanding social research will allow a better understanding of the natural world around us and the implications of the salmon aquaculture industry on different stakeholder groups and the industry overall.

This research is only a starting point to understanding the salmon aquaculture industry. More research could fine-tune the strategies from this research to obtain more data. Involving better data and further research into the real impacts of salmon aquaculture would help clarify and examine the public understanding of the industry. The industry has room for sustainable growth which would support booming populations and coastal communities. However, if how the public perceives salmon aquaculture is not understood, research may be at a loss.

Limitations

There are limitations to social media research and data collection. For example, cultural, political, and socioeconomic factors can affect the availability and representativeness of digital data (Correia et al., 2021; Jarić et al., 2020). Demographic characteristics such as age, gender, and education can also limit the social media data (Correia et al., 2021; Jarić et al., 2020). In research such as this, rural, traditional, and Indigenous societies need better representation in the digital data (Correia et al., 2021; Jarić et al., 2020). In the case of coastal research, the digital data can be sparse, and as one distances themselves from the water, the data becomes sparser (Jarić et al., 2020). The opinions of the public also have some inherent biases as perhaps we only hear the most vocal interest groups' opinions (Froehlich et al., 2017). As the data grows, it may be necessary to have further hardware requirements, or more computational know-how (Jarić et al., 2020). In addition, the spatiotemporal coverage and representativeness of the data can vary as, typically, data is only available for the lifespan of the media platform (Jarić et al., 2020). For example, Twitter started in 2006, and as such, tweets are only available from 2006 until the present day. Finally, having fewer data points can also affect the results as you only get data up to and including the day you use the code. In the case of this research, it means from 2006 up to and including August 21st of 2021. Another issue that can make working with digital data complex is that if data access changes it can also prevent the research results from being reproducible, as the original data in a study may not be recoverable (Correia et al., 2021). Firms are increasingly restricting access to their data to monetize their content, resulting in a significant gap in data available to researchers.

The complexity of language, like hashtags, synonyms, homonyms, negation, and sarcasm, can also introduce additional 'noise' that requires potential analysis and filtering prior to analysis (Correia et al., 2021). In VADER, some disadvantages have to do with language and grammar. Any misspellings or grammar mistakes may cause the analysis to miss important words or usage. Sarcasm and irony and some compound sentences can also be mis-detected as they can be very nuanced so that only a human rater may catch it, whereas code may not (Asghar et al., 2018). This analysis is very language-specific, and as such, the focus is only on English-speaking tweets. The focus of this research is around Canada, but other places may use English and tweet in English, so there may be other extraneous data in the analysis that is not filterable, and non-English discourse is left out entirely. Finally, VADER is a lexicon-based approach, and as such, it may miss certain things. For example, suppose the dictionary does not include all words or phrases. We cannot find sentiment and domain-specific words in that case, as the lexicon is more general to capture a more extensive array of data.

In terms of filtering and categorizing data, it is up to the researcher to determine which data to remove. In the research case, the first results I removed were any tweets that are retweets or replies. These were not particularly helpful to address sentiment as they are often nuanced conversations between specific users, so the choice was to remove them from the dataset. The second step was to filter out tweets that did not contain the word aquaculture. In several cases, the scraper found user tweets with 'aquaculture' in their username, regardless of if the tweet had anything to do with the topic. This step also filtered out any missing accounts or those that Twitter suspends, where their data is "@XYZ's account is temporarily unavailable because it violates the Twitter Media Policy. Learn more." This change removed 11,360 rows of data. In this step, I also dropped duplicate tweets. Then I removed users' tweets without a biography or if they had no individual stakeholder groups category. This step removed 47,208 rows. At the end of all the filtering and processing, I had a final count of 536,988 rows of data, and then 273,319 rows once neutral data was removed. When I looked at the subset of Canadian data, I was left with 3,377 tweets that were from self-identified Canadians. There are some limitations with this approach as I could not search for every single city and town in Canada. Those users who may have put their street name, or even the name of a specific reserve (Indigenous peoples) would not be captured by this coding method.

Another minor discrepancy may be a lack of knowledge about the different types of salmon aquaculture. For example, the public may not necessarily know the difference between off-shore salmon aquaculture firms versus on-shore facilities and the difference between finfish aquaculture facilities and non-finfish facilities like seaweed and shellfish aquaculture. Understanding the differences and the drivers of negative sentiment will be extremely important to tackle issues in each industry. A one-size-fits-all approach is not applicable in salmon aquaculture, and as such, research should differentiate between the different types of aquaculture industries.

Recommendations for Further Research

While this thesis includes lots of data, there is certainly room for additional data that can further research into salmon aquaculture and stakeholder management. Many study limitations have to do with the methods and programs used to analyze the data. For future research, it may be helpful to update or create a new data scraping tool from Twint. Twint is an open-source program, which means that many people add to the project to make it function. With Twitter constantly changing its API and access to its data, it may be helpful to create a new tool that can do what Twint can while improving upon other areas. A new tool could ensure that ALL tweets are collectable, and that we can scrape all necessary metadata from the site. It would also improve the replicability of the data and ensure that future research can support and further this research.

Another exciting facet of this research is the categorization of Twitter users into stakeholder groups. We place users in categories due to their use of key phrases and words within their Twitter bios. However, not everyone has a bio, and not everyone's bio leads to an easy method of determining what kind of stakeholder they might be regarding the topic of interest. If a different method were used (perhaps machine learning) there might be a better way to improve this categorization. It would also be interesting to further break down categories into sub-categories within the stakeholder groups like splitting based on geographical location, age or maybe even gender for a comparison. A geographical comparison would be great for comparing Canada to similar countries with aquaculture policy to see if our aquaculture is following similar sentiment trends or if the industry is headed toward failure if sentiment is decreasing.

Further research might also include other keywords to obtain a larger dataset. For example, it might be interesting to focus purely on aquaculture in relation to fish species other than salmon or on specific countries or issues about salmon aquaculture. A broader focus ensures that researchers can gather all tweets on the topic, and perhaps a better overview of sentiment is explorable. Exploring different sentiment analysis and scraping tools may offer an interesting comparison to verify the overall sentiment of a dataset. Such research aims to further the iEcology field and allows for the examination of more environmental data and data sets.

Exploring different temporal scales would offer greater insight into sentiment at specific moments in time. Studying long-term trends of public sentiment toward aquaculture may offer a useful insight into different stakeholders' opinions and thoughts. It would be interesting to look at how the sentiment of tweets overall compares to the sentiment of aquaculture tweets specifically. This would also help in cross-sectional studies to look at sentiment around specific events that have occurred in the realm of aquaculture. This could be an event like a major lawsuit, a policy change, moratoriums placed on fish farming, and so on.

CONCLUSION

In a nation like Canada, we need to consider many aspects to remain just, environmentally friendly, and prosperous. The goal of this thesis is to offer more data to a newer and changing industry. There are not many resources for aquatic ecosystems. A significant aspect of this thesis is to explore the connection between online social media data and the salmon aquaculture industry and its stakeholders. This thesis uses software-assisted analysis of large volumes of data about public discourses to provide insights into how different groups of stakeholders perceive salmon aquaculture over time, and in different places like Canada. The question(s) I explored are: How does public sentiment towards salmon aquaculture differ over time? And how does public sentiment towards salmon aquaculture differ among stakeholder groups?

Understanding the sentiment of stakeholders within the salmon aquaculture industry is necessary to understand the *what* and the *why* behind their views and opinions. These data offer a considerable development for future analysis. Now that sentiment is trackable, we can parse data to determine how the slightly negative sentiments can improve and how the industry can improve its relationships with stakeholders and their industry views. Improving the industry's sentiment will hopefully indicate better policies, further sustainability in the industry, and a lack of major issues like pollution, fish escapes, and loss of diversity within ecosystems. When you look at most events from 2006 to 2021 in the salmon aquaculture industry, one would expect the results of stakeholder opinion to be largely negative. Many significant events impact several stakeholder groups, from researchers to workers to Indigenous peoples. However, the data trends positively over time and tends to skew to the positive side for most stakeholder groups in most years.

The dataset of 273,319 individual, unique tweets is divided into four main categories to address the research question(s). The categories are overall sentiment, sentiment from year to year (2006-2021), sentiment by stakeholder category and sentiment by stakeholder category per year. The overall sentiment category has a mean of 0.3, a median of 0.4, and a standard deviation of 0.4. This data is consistent and clusters around the mean. Table 2 calculates a skewness value of -0.994 for the overall dataset, which is a moderate negative skew. An R-squared value of 0.79 relates to an absolute strong model, meaning that this data is reasonably representative of the stakeholder groups and their opinions. All eight stakeholder group categories display a moderately negative skew (Table 4). All categories have a positive mean sentiment, and the graphs tend to lean on the positive sentiment side. For example, the Academic group graphs and data display an absolute strong model, the industry group displays a moderate-strong model, and the ENGO group displays a weak-moderate model. In contrast, the other five stakeholder groups display a very weak model, which indicates a lack of strong data.

The findings in this paper help create an open dialogue with non-statutory stakeholders and find governance solutions that benefit all Canadians. This data will also enable a means for further research and collaboration with all salmon fisheries and farms to create a solid structure for the governance of the salmon aquaculture industry. Future research can be more specific, or even broader depending on the needs of the industry or the data provided by the method. Testing further independent variables alongside sentiment and time could offer interesting insights into different stakeholder groups, as well as different time periods in the history of aquaculture.

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APPENDIX A - Salmon Aquaculture Timeline

The 1800s

- 1857: First detailed records of planned aquaculture activity in Canada (GoC, 2015)
- 1884: The first hatchery in B.C. for Pacific salmon was established at Harrison

The 1900s

- 1950: Federal and provincial hatcheries produce ~750 million freshwater trout and salmon annually for wild stock enhancement (GoC, 2015)
- 1970s: Salmon farming begins on the Sunshine Coast in B.C. (Macdonald, 2011)
- 1970: DFO research leads to development of salmon and trout aquaculture (GoC, 2015)
- 1972: On the West Coast salmon farming is first established (GoC, 2015), (Page, 2007, pg. 615)
- 1975: James Bay Agreement of 1975 (VanderZwaag, 2006, pg. Ch.10 2/17)
- 1980s: Norwegian salmon farming companies enter B.C., buying and consolidating small operations. Introduction of Atlantic salmon species to the region (Macdonald, 2011)
- 1980: Commercial scale marine finfish aquaculture operations begin in Canada. (GoC, 2015)
- 1980: Atlantic salmon in B.C. quickly dominates the industry (GoC, 2015)
- 1980s: Toxic algae blooms devastate fish inventories (Macdonald, 2011)
- 1984: Canadian aquaculture policy emerged in its modern form (Rayner & Howlett, 2007, pg51)
- 1986: Inquiry into Finfish Aquaculture in B.C. (VanderZwaag & Chao, 2002, pg. 328)
- 1986: First Ministers' Conference in 1986 (Rayner & Howlett, 2007, pg. 60)

- 1986: The government declares a moratorium on new aquaculture licenses and organizes an inquiry into the industry (Macdonald, 2011)
- 1987: Moratorium on new licenses lifted (Macdonald, 2011)
- 1988: Canada/B.C. Memorandum of Understanding on Aquaculture Development is signed (VanderZwaag, 2006, pg. 4/58), (Macdonald, 2011)
- 1988: Ombudsman Public Report No.15: Aquaculture and the Administration of Coastal Resources in B.C. (VanderZwaag, 2006, pg. 20/58)
- 1988: Simon Fraser University creates an aquaculture research institute and later the University of B.C. creates a Chair of Aquaculture Research (Macdonald, 2011)
- 1989: A large windstorm damaged some salmon farms in B.C., leading to the escape of 100,000 farmed Atlantic salmon. Many farms also suffered from toxic algal blooms, resulting in the deaths of thousands of farmed fish (Page, 2007, pg. 615)
- 1989: B.C. has its strongest sockeye salmon run in 76 years. Increased supply results in a drop in price and many salmon farms go bankrupt (Macdonald, 2011)
- 1990: Industry moves from the smaller independent farm model to more consolidated ownership (GoC, 2015). B.C. went from 100 companies in 1988 to only 12 in 2003. (Rayner & Howlett, 2007, pg. 55)
- 1991: The US levies an anti-dumping tariff on Norwegian salmon (Macdonald, 2011)
- 1994: Sea lice from salmon farms are identified as the sole cause of the Irish sea trout collapse, prompting calls in the B.C. media for a federal or provincial review of the environmental impact of salmon farming. (Macdonald, 2011)
- 1995: The B.C. government and DFO places a moratorium on new farm licenses and announces the creation of the Salmon Aquaculture Review Panel (Macdonald, 2011)
- 1997: The Province of B.C. released the “Salmon Aquaculture Review Report” (GoC, 2015)

- 1999: Increasingly high numbers of escapes from farming pens in B.C. lead to the creation of the provincial Salmon Aquaculture Policy Framework (GoC, 2015)
- 1990: Sparrow Case (VanderZwaag, 2006, pg. Ch.10 2/17)
- 1993: Wild and Farmed Salmon and Interactions: Review of Potential Impacts and Recommended Action (VanderZwaag & Chao, 2002, pg. 328)
- 1995: B.C.'s provincial government creates a moratorium on new licenses to allow for an environmental assessment of aquaculture (Flaherty et al., 2019)
- 1995: Release of a Federal Aquaculture Strategy
- 1995-2002: Between 1995 and 2002, the province decided to impose a moratorium on new salmon farms, and capped coastal salmon farm tenures at 121. (VanderZwaag, 2006, pg. 13/58)
- 1995: Food and Agriculture Organization's (FAO) Code of Conduct for Responsible Fisheries was adopted (VanderZwaag & Chao, 2002, pg. 283)
- 1995: The Canadian Aquaculture Industry Alliance (CAIA), formed (Rayner & Howlett, 2007, pg. 61)
- 1995: Salmon Aquaculture Review (VanderZwaag & Chao, 2002, pg. 328)
- 1996: Fisheries Act of 1996 (FAO, 2019)
- 1996: Environmental Effects of Salmon Net Cage Aquaculture in B.C. (VanderZwaag & Chao, 2002, pg. 328)
- 1996: Commercial fishing rights trilogy (VanderZwaag, 2006, pg. Ch.10 2/17)
- 1997: Province of B.C. released the "Salmon Aquaculture Review Report" (DFO, 2019)
- 1997: The Oceans Act expanded DFO's role in the development of ocean resources (VanderZwaag, 2006, pg. 9/32)
- 1997: Delgamuukw case (Macdonald, 2011)
- 1998: The first evidence of successful Atlantic salmon spawning was discovered in the Tsitika River on Vancouver Island (Macdonald, 2011)

- 1999: The Alaskan government publishes a white paper on its concerns about B.C. salmon farming and begins to lobby the B.C. and Canadian governments to continue the moratorium on salmon farming. (Macdonald, 2011)
- 1999: Canadian Environmental Protection Act (Milewski & Smith, 2019, pg. 2)
- 1999: CCFAM was responsible for the negotiation of the Agreement on Interjurisdictional Cooperation with Respect to Fisheries and Aquaculture in 1999, creation of Aquaculture Task Group (ATG) (Rayner & Howlett, 2007, pg. 60) (VanderZwaag & Chao, 2002, pg. 300)
- 1999: Marshall decision (VanderZwaag, 2006, pg. Ch.10 2/17)
- 1999: Creation of the provincial Salmon Aquaculture Policy Framework (DFO, 2019)

2000 to Today

- 2000: Aquaculture now occurs in all provinces and Yukon, and production has increased more than four-fold over the last 20 years (GoC, 2015)
- 2000: Conference on Aquaculture in the Third Millennium (VanderZwaag & Chao, 2002, pg. 283)
- 2000: September 2000 Aquaculture Conference at the Rodd Brudenell River Resort in Montague, P.E.I. (Crowley, 2002, pg. 1)
- 2000: Nisga'a Treaty of 2000. (VanderZwaag, 2006, pg. Ch.10 2/17)
- 2000 The Coastal Alliance for Aquaculture Reform (CAAR) is formed (Macdonald, 2011)
- 2001: Judge Stewart Leggatt conducted a series of public hearings on salmon farming in October 2001 (Page, 2007, pg. 619)
- 2001: The GoC Discussion Document on the Precautionary Approach/Principle' was released in 2001 (VanderZwaag & Chao, 2002, pg. 308)
- 2001: Legislative & Regulatory Review of Aquaculture in Canada (Crowley, 2002, pg. vi)
- 2001: February 2001 Aquaculture Conference in B.C.. (Crowley, 2002, pg. 1)

- 2001 The federal Auditor General announces that the federal government is failing to protect wild B.C. salmon stocks from farmed salmon (Macdonald, 2011)
- 2002 The moratorium placed on new site licenses in 1995 is lifted (Macdonald, 2011)
- 2002: Finfish Aquaculture Waste Control Regulation (FAO, 2019)
- 2002: The B.C. government announced that it would accept applications for new salmon aquaculture sites given improved provisions for siting and relocations, research and development, and fish escapes, health, and waste. (VanderZwaag, 2006, pg. 13/58)
- 2002: First Nation and environmentalist demonstrators dumped rotting salmon on lawns of the B.C. legislature to protest the planned lifting of the 1995 moratorium. (Page, 2007, pg. 615)
- 2002: BCAFC hold a public summit on salmon farming (Page, 2007, pg. 618)
- 2002: Announce the launch of the West Coast Vancouver Island (WCVI) Aquatic Management Board (VanderZwaag & Chao, 2002, pg. 325)
- 2003: The Heiltsuk led an ‘International Day of Protest’ to dispute Omega’s Atlantic salmon hatchery (Page, 2007, pg. 616)
- 2003: The Heiltsuk First Nation initiates a lawsuit against the B.C. government and PanFish (Macdonald, 2011)
- 2003: The Nuxalk Nation launched a boycott of Canada Safeway and Real Canadian Superstore to protest sale of farmed salmon, placing ‘Farmed and Dangerous’ stickers on packages of farmed salmon for sale in the store. (Page, 2007, pg. 616)
- 2003: Sierra Legal Defense Fund launched a lawsuit on behalf of four First Nations in the Broughton Archipelago charging that the governments have failed to protect aboriginal rights, including the right to fish. (Page, 2007, pg. 616)
- 2003: An international workshop examining sea lice research is organized by UBC (Macdonald, 2011)

- 2004: “Science” (one of the foremost scientific journals) publishes an article by Hites examining the links between farmed Atlantic salmon and toxins (Macdonald, 2011)
- 2005: B.C. Salmon Farmers Association established a Code of Practice (FAO, 2019)
- 2005 Members of the B.C. Wilderness Tourism Association demand the fallowing of fish farms in the Broughton Archipelago (Macdonald, 2011)
- 2006: CAAR and Marine Harvest announce an agreement to conduct joint research (Macdonald, 2011)
- **2007: Ahousaht First Nation vs Canada (Pinkerton, 2014 pg. 2)**
- **2007: B.C. Supreme Court upholds Creative Salmon of Tofino’s successful libel/defamation suit against Don Saniford (Macdonald, 2011)**
- **2007: A study, published on-line by Martin Krkosek using 40 years of DFO data suggests that sea lice from salmon farms killed 95% of wild juvenile smolts (Macdonald, 2011)**
- **2007: 18 respected scientists and researchers send an open letter to the PM and the Premier calling for immediate barriers between wild and farmed salmon (Macdonald, 2011)**
- **2008: (Huppert, 2005) The province placed a moratorium on all finfish aquaculture development along B.C.’s North Coast (north of Klemtu) because of concerns about the potential impact on wild salmon stocks.**
- **2008: Federal Law on Sustainable Development Act (Milewski & Smith, 2019, pg. 2)**
- **2008: Research by Dalhousie scientists Ford and Myers reports that fish farms are associated with plummeting populations of salmon and trout (Macdonald, 2011)**
- **2008: 2,500 salmon escape from a farm in Clayoquot Sound (Macdonald, 2011)**

- **2008: 30,000 salmon escape from a Marine Harvest farm near Campbell River (Macdonald, 2011)**
- **2008-2009: Sea-lice levels dropped between 2008 and 2009 on young pink and chum salmon migrating through the Broughton Archipelago (Macdonald, 2011)**
- **2009: Provincial government creates the Pacific Salmon Forum to study the health of wild salmon (Macdonald, 2011)**
- **2009: Alexandra Morton sends letter and petition to federal Fisheries Minister Gail Shea asking her to apply the Fisheries Act to the "salmon feedlot fishery" (Macdonald, 2011)**
- **2009: In 2009, the B.C. Supreme Court ruled in Morton v B.C. (Agriculture and Lands) decision that fish farms are not farms, but are fisheries, and that the Federal Government had exclusive jurisdiction over most aquaculture activities (Flaherty et al., 2019; Huppert, 2005; Pynn 2009)**
- **2009: The B.C. The Supreme Court (Justice Chris Hinkson) ruled that the federal government -- not the province -- has exclusive jurisdiction over the management of salmon farming. (Macdonald, 2011)**
- **2009: Marine Harvest announces it is appealing the B.C. The Supreme Court ruled that the federal government, not the province, has jurisdiction over fish farms, claiming that "Domesticated creatures, like farm raised salmon, are private property, and are not part of the fishery as a public resource." (Macdonald, 2011)**
- **2009: Canada's continued low ranking (23rd) among world aquaculture producers triggered DFO to lead a nation-wide consultation. The consultation resulted in the formulation of the National Aquaculture Strategic Action Plan Initiative (2011–2015) (Milewski & Smith, 2019, pg. 2)**
- **2009: First Nations in the Broughton Archipelago announce they will file a class-action lawsuit against the B.C. government (Macdonald, 2011)**

- **2009: While some parts of the province have strong sockeye runs, the Fraser River sockeye run collapses. Record runs of pink salmon (Macdonald, 2011)**
- **2010: PM Stephen Harper initiated a two-year-long, $26 million (CAD) inquiry (Cohen Commission) led by Justice Bruce Cohen to investigate the declines (Viatori, 2019) (Macdonald, 2011)**
- **2010: The Canada-B.C. agreement on aquaculture management**
- **2010: Taras Grescoe's book *Bottom feeder: A seafood lover's journey to the end of the food chain is published in Canada*. It claims that sea lice are wiping out wild salmon (Macdonald, 2011)**
- **2012: DFO Report: *Aquaculture Sustainability Reporting Initiative*, announcing its intention to develop sustainability indicators (SI) for aquaculture (Milewski & Smith, 2019, pg. 2)**
- **2013: Ahousaht et al. vs Canada (Pinkerton, 2014 pg. 2)**
- **2014: FAO report on The State of World Fisheries and Aquaculture (Bankes, pg. 1)**
- **2016: Formation of the Minister of Agriculture's Advisory Council on Finfish Aquaculture (MAACFA) by B.C. (MAACFA, 2018 pg. 1)**

The Future of Aquaculture

- **2020: Moratorium on the expansion of salmon tenures in the Discovery Islands area that will last until September 30, 2020 (Flaherty et al., 2019).**
- 2022: By 2022, prior to issuing a new tenure or a renewal of a tenure, B.C. will require that open-net pen salmon farms meet specific criteria (Government of B.C., 2018).
- 2022: 79% of finfish farm sites (95) have federal (DFO) licenses with an expiry date of 2022 (Government of B.C., 2018).

APPENDIX B - Query Code Script

The following command was run for each year, from 2006, up to and including 2021:

```
for run in {1..5000}; do ./scrape_twitter 2006 "aquaculture"; done
```

The script that was run was:

```
scrape_twitter
#!/bin/bash
twint -s "$2" \
  --csv -o "/Volumes/Seagate/thesis_twitter_scraping/$2$1.csv" \
  --resume "/Volumes/Seagate/thesis_twitter_scraping/$2$1.csv" \
  --since "$1-01-01" --year "$(($1+1))"
```

This script calls the twint command. The '*-s'* flag denotes a search query and '*$2'* resolves as the keyword "aquaculture". Other terms, such as `fish farming,' do not significantly increase sample size and tend to be captured by the "aquaculture" search term (Froehlich et al., 2017). The '*--csv'* flag writes the scraped tweets into the CSV format. '*-o'* flag designates the return file. In the script, '*$2$1*' represents the first and second command line arguments. In this case '*$1'* is the year, and '*$2'* is the query "aquaculture". So, the file names will resemble "aquaculture2021.csv", for example. The '*--resume*' flag allows the scraper to pick up where it left off. This is an important feature because Twint consistently stops scraping tweets early. It is possible that the sparse data being returned from the query in earlier years causes this issue. Regardless, resuming from where it left off allows repeated calls to this script to eventually extract all the tweets with the keyword "aquaculture" for the given year. The '*--since'* flag denotes a start date for the extracted tweets. The '*$1'* in the string is the first command line argument, which in this case is the year to be scraped. This resolves as *–since "2021-01-01*", for example. The '*--year'* tag in this case is a bit confusing: it specifies that tweets BEFORE that year are to be scraped. Alternatively, it is an upper bound on the year of tweets. Regardless, "*$(($1+1))*" is one more than the specified year. For instance, if ‘*$1’* is 2021, this resolves to --*year "$2022*". Combining the ‘--*since*’ and ‘--*year*’ tags together allow a single year of tweets to be extracted at a time.

The for/do loop is used to run the script many times. Because Twint often stops scraping data, despite there being more data within that year to scrape, it is necessary to create a loop to keep resuming the data collection. Calling Twint with ‘--*resume’* allows it to pick up from where it left off. Calling Twint again after it stopped scraping writes to the same file. Repeated calls to the command yield all the tweets from the query “aquaculture” for each year.

APPENDIX C - Coding with Pandas and Colab

```
import csv
import pandas as pd
import nltk
import datetime
import numpy as np
import re
from nltk.corpus import stopwords
from nltk.sentiment.vader import SentimentIntensityAnalyzer
nltk.download('vader_lexicon')
```

Figure C 1. Import programs and code bases to Google Colab

```
from google.colab import drive
drive.mount('/content/gdrive')
```

Figure C 2. Authorizing and mounting Google Drive files to Google Colab

```
bios = pd.read_csv('//content/gdrive/MyDrive/Colab Notebooks/bios.csv')
```

Figure C 3. Connecting the bios file to the cleaned-up data

```
def is_canada(bios):
  # lowercases the location from the bio, strips non-letters, and splits into words
  location = bios.location.str.lower().fillna('')
  location = location.str.replace('[^a-zé]', '').str.split()

  # In the case of 'québec', we need to do better than [^a-z]

  def has_canadian_word(location_list):
      CANADIAN_WORDS = [
          'canada','alberta', 'british columbia', 'manitoba', 'new brunswick',
          'newfoundland', 'labrador',
          'nova scotia', 'ontario', 'prince edward island','québec', 'saskatchewan',
          'nunavut', 'northwest territories', 'yukon',
          'ab', 'bc', 'mb', 'nb', 'nl', 'nfl', 'ns', 'on', 'pei', 'qc', 'sk', 'nu',
          'nt', 'nwt', 'yt',
          'toronto', 'ottawa', 'missisauga', 'guelph', 'barrie', 'sudbury', 'brantford',
          'kingston', 'cambridge', 'kitchener', 'waterloo', 'niagara falls', 'sault ste. marie',
          'thunder bay', 'vaughan', 'windsor', 'woodstock', 'timmins', 'quinte west', 'pickering',
          'peterborough', 'pembroke', 'owen sound', 'oshawa', 'orillia', 'markham', 'hamilton',
          'brockville', 'belleville',
          'calgary', 'edmonton', 'strathcona county', 'medicine hat', 'red deer',
          'vancouver', 'surrey', 'burnaby', 'kelowna', 'courtenay', 'coquitlam', 'kamloops',
          'langford', 'langley', 'nanaimo', 'richmond', 'surrey',
          'winnipeg', 'brandon', 'springfield', 'dauphin', 'flin flon', 'morden', 'portage la prairie',
          'steinbach', 'winkler',
```

```
        'moncton', 'saint john', 'fredericton', 'bathurst', 'miramichi',
        "st johns", 'conception bay', 'mount pearl', 'corner brook',
        'yellowknife', 'hay river', 'inuvik',
        'halifax', 'lunenburg', 'dartmouth',
        'iqaluit', 'arivat', 'rankin inlet',
        'charlottetown', 'summerside',
        'montréal', 'laval', 'hull', 'gatineau',
        'saskatoon', 'regina',
        'whitehorse', 'dawson city', 'faro',
    ]
    return bool(set(CANADIAN_WORDS) & set(location_list))

  return location.apply(has_canadian_word)
bios['is_canada'] = is_canada(bios)
```

Figure C 4. Sorting overall data by Canadian locations

```
dataframes = {}

tweet_dtypes = { 'id': int, 'user_id': int, 'username': str, 'name': str, 'place':str, 'date': str, 'time': str,
'tweet': str, 'language': str, 'mentions': str, 'urls': str, 'replies_count': int, 'retweets_count': int,
'likes_count': int, 'hashtags': str, 'retweet': bool }

for year in range(2006, 2021 + 1):
  dataframes[year] =
pd.read_csv(f'/content/gdrive/MyDrive/aquaculture_data/clean_data/aquaculture{year}.c
sv', dtype=tweet_dtypes, usecols=tweet_dtypes)
tweets = pd.concat(dataframes.values())
print(f"tweets has {len(tweets)} rows")
tweets = tweets.drop_duplicates()
print(f"tweets has {len(tweets)} rows after drop_duplicates")
```

Figure C 5. Code to Tidy-up CSV files

```
combined = tweets.rename(columns={'id': 'tweet_id'}).merge(
  right=bios.rename(columns={'id': 'user_id'}),
  how='left',
  on=['user_id'],
  suffixes=['_from_tweet', '_from_bio'],)
```

Figure C 6. Combine Tweets CSV with Bios CSV

```
contains_aquaculture = combined.tweet.str.lower().str.contains('aquaculture')
print(f'Filtering rows without "aquaculture" in the tweet. {sum(~contains_aquaculture)}
rows will be filtered, reducing the row count from {len(combined)} to '
```

```
    f'{len(combined) - sum(~contains_aquaculture)}
({100 *sum(contains_aquaculture) / len(combined):.2f}
% of rows will be retained)')
combined = combined[contains_aquaculture]
```

Figure C 7. Filtering tweets to exclude unnecessary data

```
print(f'{sum(combined.username_from_bio.isnull())} rows without a bio ({100 *
sum(combined.username_from_bio.isnull()) / len(combined):.2f}%). Filtering.')
combined = combined[~combined.username_from_bio.isnull()]
```

Figure C 8. Filtering data rows without a bio for a user

```
print("reapplying types, rearranging columns, dropping unnecessary columns.")
dtypes = {'tweet_id': int, 'user_id': int, 'username_from_tweet': str, 'username_from_bio': str,
'name_from_tweet': str, 'name_from_bio': str, 'date': str, 'time': str,'tweet': str, 'bio': str, 'location': str,
'language': str, 'followers': int, 'likes': int, 'category': str}

combined = combined[dtypes].astype(dtypes)
df = combined
```

Figure C 9. Rearranging columns and dropping unnecessary data

```
combined.loc[combined['category_A'], 'category'] = 'A. Academic / Researcher'
combined.loc[combined['category_B'], 'category'] = 'B. Industry / Worker'
combined.loc[combined['category_C'], 'category'] = 'C. ENGO / Conservation'
combined.loc[combined['category_D'], 'category'] = 'D. Government'
combined.loc[combined['category_E'], 'category'] = 'E. Indigenous'
combined.loc[combined['category_F'], 'category'] = 'F. Media'
combined.loc[combined['category_G'], 'category'] = 'G. Other'
combined.loc[combined['category_H'], 'category'] = 'H. No Category
```

Figure C 10. Collapsing the stakeholder categories into columns for easier data manipulation

```
!pip install langdetect
import pandas as pd
import csv
from typing import Set
import re
import langdetect
```

Figure C 11. Which tools to install and import for Colab

```
from google.colab import drive
drive.mount('/content/gdrive')
```

Figure C 12. Mounting the Google Drive

```
dtypes = {'id': int, 'name': str, 'username': str, 'bio': str, 'url': str, 'tweets': int, 'following': int, 'followers': int, 'likes': int, 'verified': bool, 'private': bool, 'location': str}
bios = pd.read_csv('/content/gdrive/MyDrive/aquaculture_data/bios/clean_user_bios.csv', quoting=csv.QUOTE_NONNUMERIC, escapechar="\\", doublequote=False, dtype=dtypes, usecols=dtypes)
bios = bios[~bios['bio'].isnull()]
```

Figure C 13. Datatypes and reading in CSVs

```
def contains_word_in_keywords(bio: str, keywords: Set[str]) -> bool:
 keywords = {word.lower() for word in keywords}
 bio = bio.lower().replace('-', '').replace('"', '')
 for keyword in keywords:
   if keyword in bio:
     return True
 return False

def is_researcher(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'researcher', 'analyst',  'investigator', 'scientist', 'science', 'scientific', 'experimenter', 'tester', 'ecologist','biologist', 'lab', 'laboratory', 'ecology', 'biology', 'geology', 'geologist', 'agronomist', 'archeologist', 'entomologist','anthropologist','ichthyologist', 'archaeologist', 'virologist', 'pharmacologist', 'fieldwork', 'historian', 'geography', 'GIS'})

 def is_academic(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'academic', 'academia', 'scholar', 'class', 'teacher', 'teach' 'educate', 'educator', 'educate', 'education', 'professor', 'student', 'academic','university', 'college', 'postdoc','PhD', 'MSc', 'MBA', 'BSc', 'bachelor', 'major', 'undergrad', 'graduate', 'post graduate', 'alumni', 'alumna','alumnus', 'school', 'faculty', 'lecturer','instructor', 'learner', 'learning', 'institute'})

def is_company(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'company', 'business', 'firm', 'facility', 'enterprise', 'industry', 'industries', 'private sector', 'establishment', 'outfit','processors', 'production', 'product','founder', 'startup', 'seafood', 'serving', 'owner', 'CEO', 'CFO', 'COO', 'VP', 'president','manager', 'director', 'management', 'entrepreneur', 'freelance', 'executive', 'innovator','manufacturer', 'insurance', 'aquaponics','suppliers', 'importer','supplying'})

def is_ngo(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'ENGO' , 'NGO', 'IUCN', 'WWF', 'CWRA', 'not for profit', 'nonprofit', 'self organization', 'nongovernment', 'nongovernmental','association', 'united nations',
```

```
'outreach', 'climate', 'initiative', 'steward', 'stewardship', 'fellowship','organization', 'organization',
'future generations'})

def is_worker(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'worker', 'working', 'work', 'employed', 'employee', 'laborer',
'hand', 'help', 'blue collar', 'tradesperson', 'white collar','working person', 'career', 'staff', 'staffing',
'engineer', 'job', 'corporate', 'engineer', 'IT', 'vet', 'veterinary',
'veterinarian','consultancy','consulting','marketing', 'communication', 'PR', 'HR', 'career', 'advisor',
'programming', 'developer','consultant', 'designer', 'physicist', 'firefighter', 'actor', 'actress', 'attorney',
'contractor', 'coder', 'surgeon', 'doctor', 'Dr', 'nurse', 'accountant', 'sales', 'retired'})

def is_activist(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'activist', 'lobby', 'lobbyist', 'advocate', 'opponent', 'injustice',
'revolutionary', 'sustainable', 'sustainability', 'sustainably', 'sustained' 'volunteer', 'steward', 'inform',
'concerned citizen', 'change agent','change maker', 'disruptor', 'UNESCO' })

def is_indigenous(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'Indigenous', 'aboriginal', 'native', 'ancestral', 'chief', 'tribal',
'blackfoot', 'Kjipuktuk'})

def is_government(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'parliament', 'governance', 'congress', 'senator', 'senate',
'government', 'federal', 'national', 'county', 'regional', 'global', 'provincial', 'municipal', 'bureaucracy',
'politics', 'politician', 'political', 'councillor', 'chancellor', 'governor', 'MP', 'MPP', 'policy', 'regulation',
'regulatory', 'ministry', 'law', 'state', 'control', 'rule', 'FAO', 'DFO', 'public sector', 'office of', 'bureau',
'magistrate', 'legislative', 'diplomat', 'public servant', 'republican', 'democrat', 'patriot', 'conservative',
'liberal', 'libertarian', 'minister', 'commissioner', 'deputy', 'mayor'})

def is_conservationist(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'conservationist', 'conservation', 'conservancy', 'conserving',
'conserve', 'environment', 'environmentalist', 'environmental', 'Guardian', 'preservationist',
'naturalist','treeHugger', 'tree', 'eco', 'ecosystem', 'bio', 'green', 'nature', 'botany', 'horticulture',
'wildlife', 'local', 'advocate', 'advocacy','activism', 'activist', 'humanitarian' 'blue revolution', 'green
revolution', 'hippy', 'future generations', 'renewable energy'})

def is_fisher(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'fisherman', 'fishing', 'angling', 'sailing', 'sailor', 'farmer',
'farm', 'crop', 'agriculture', 'agricultural', 'angler', 'trawler', 'boat', 'fisher','Rodman', 'Piscator', 'hunter',
'rancher', 'hunting', 'diver', 'diving'})
```

```
def is_media(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'media', 'journalist', 'reporter', 'reporting', 'correspondent', 'advertisers', 'article', 'magazine', 'newspaper', 'tabloid', 'press', 'photographer', 'photography', 'TV', 'television', 'radio', 'podcast', 'journal', 'host', 'writer', 'publish', 'book', 'poet ', 'artist', 'editor', 'author', 'novel', 'blogger', 'blog', 'technology', 'official', 'news', 'gazette'})

def is_water(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'water', 'H2O', 'underwater', 'ocean', 'sea', 'river', 'greatlake', 'lake', 'aquaculture', 'aquaculturist', 'aquatic', 'fish','marine', 'wetland', 'estuaries', 'coast', 'MPA', 'wild', 'salmon', 'reef', 'maritimes', 'atlantic', 'pacific', 'aquarium','wastewater','coastline',})

def is_gamer(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'D&D', 'game', 'gaming', 'gamer', 'player', 'minecraft', 'mod', 'Blizzard', 'warcraft', 'MMORPG', 'steam', 'discord', 'battletag', 'twitch', 'gadget', 'CoD'})

def is_tech(bio: str) -> bool:
 return contains_word_in_keywords(bio,  {'tech', 'web', 'blockchain', 'crypto', 'finance', 'investor', 'investment', 'invest', 'stocks', 'trading','coin', 'NFT', 'financial'})

def is_prepper(bio: str) -> bool:
 return contains_word_in_keywords(bio, {'prepper', 'prepping', 'survivalist', 'homesteading' })

def is_foodie(bio: str) -> bool:
 return contains_word_in_keywords(bio,  {'vegan', 'veganism', 'vegetarian', 'eat', 'food', 'foodie', 'dishes', 'chef', 'gourmet', 'culinary','brewery', 'restaurant', 'connoisseur', 'eats', 'baker', 'restauranteur', 'organic', 'natural','supermarket', 'grocery', 'grilling', 'cuisine', 'artisanal', 'BBQ'})

def is_family(bio: str) -> bool:
 return contains_word_in_keywords(bio,  { 'daughter', 'son', 'mother', 'mom', 'momma', 'mama', 'mum', 'sister', 'brother', 'father', 'dad', 'papa', 'wife', 'husband', 'aunt', 'uncle', 'cousin', 'family','kid', 'child', 'grandmother', 'grandfather', 'grandma', 'grandpa', 'granddad'})

def is_non_ascii(bio: str) -> bool:
 return not bio.isascii()

def is_non_english(bio: str) -> bool:
 try:
  return not langdetect.detect (bio) == "en"
```

```
 except(langdetect.LangDetectException) as e:
   return True

assert is_academic('I am a student.')
assert is_worker('white-collar NGOs are stupid')
assert is_ngo('white-collar NGOs are stupid')
assert is_government('the provincial government is #failing us!')
assert is_indigenous('the aboriginal groups needs to step-up now...')
assert is_media("I really don't want to work as a journalist today")
assert is_activist('my opponents really do not know how to handle this')
assert is_conservationist('conservationists')
assert not is_conservationist('I really like comic con')
assert is_fisher('#rod-man')
assert is_non_ascii ('ë ')
assert is_non_ascii ('üçÄ#contestlover üçÄ#foodie üçÄ#travellerüçÄ
#gadgetloverüçÄüçÄüçÄüçÄüçÄüçÄüçÄ')
assert not is_non_ascii ('Gizmag is now @nwtls')
assert is_non_english ('fisch')
assert is_non_english ('suivez toute l\'actualit')
assert not is_non_english ('a fire worth burning for')
```
Figure C 14. Organizing Twitter bios into stakeholder groups by keyword identification

```
bio_categorizors = [is_researcher, is_academic, is_company, is_ngo, is_worker,
is_activist,is_indigenous, is_government, is_conservationist, is_fisher, is_media,is_water, is_gamer,
is_tech, is_prepper, is_foodie, is_family, is_non_ascii, is_non_english]

skip_after_computed_once = {is_non_english}
for bio_categorizor in bio_categorizors:
 if bio_categorizor in skip_after_computed_once and bio_categorizor.__name__ in bios:
    continue
 bios[bio_categorizor.__name__] = bios['bio'].apply(bio_categorizor)
```

Figure C 15. Code for running the categories more efficiently and skipping recomputation

```
pd.set_option ('display.max_colwidth', None)
has_category = bios.is_researcher
for bio_categorizor in bio_categorizors[1:]:
 has_category = has_category | bios[bio_categorizor.__name__]
bios['is_other'] = ~has_category
```

Figure C 16. Code for determining if the bio has a category

```
bios['category_A'] = bios.is_researcher | bios.is_academic
bios['category_B'] = ~bios.category_A & (bios.is_company | bios.is_worker | bios.is_fisher)
bios['category_C'] = ~bios.category_A & ~bios.category_B & (bios.is_ngo | bios.is_conservationist |
bios.is_water | bios.is_activist)
bios['category_D'] = ~bios.category_A & ~bios.category_B & ~bios.category_C &
(bios.is_government)
bios['category_E'] = ~bios.category_A & ~bios.category_B & ~bios.category_C & ~bios.category_D
& (bios.is_indigenous)
bios['category_F'] = ~bios.category_A & ~bios.category_B & ~bios.category_C & ~bios.category_D
& ~bios.category_E & (bios.is_media | bios.is_tech | bios.is_gamer)
bios['category_G'] = ~bios.category_A & ~bios.category_B & ~bios.category_C & ~bios.category_D
& ~bios.category_E & ~bios.category_F & (bios.is_prepper | bios.is_foodie | bios.is_family |
bios.is_non_ascii | bios.is_non_english)
bios['category_H'] = ~bios.category_A & ~bios.category_B & ~bios.category_C & ~bios.category_D
& ~bios.category_E & ~bios.category_F & ~bios.category_G & (bios.is_other)
```

Figure C 17. Consolidating sub-categories into main categories from A to H

```
bios.to_csv('bios.csv')
```

Figure C 18. Exporting to Excel CSV

```
sid = SentimentIntensityAnalyzer()
df['sentiment'] = df['tweet'].apply(lambda tweet: sid.polarity_scores(tweet)['compound'])
```

```
# df['normalized_tweet_sentiment'] = df['normalized_tweet'].apply(lambda tweet:
sid.polarity_scores(tweet)['compound'])
```

Figure C 19. Running VADER sentiment analysis code on the dataframe

```
import csv
df.to_csv('complete_sentitment_analysis_data.csv', sep=',', escapechar='\\',
quoting=csv.QUOTE_ALL)
```

Figure C 20. Downloading the complete CSV file

APPENDIX D - Bios Code Script

```
import twint.run
import twint.config
import twint.token
import time
import random
from pathlib import Path
import pandas as pd
import threading
import csv
import multiprocessing
import numpy as np

BEARER =
'AAAAAAAAAAAAAAAAAAAAANRILgAAAAAAnNwIzUejRCOuH5E6I8xnZz4puTs%3D1Zv7ttfk8LF81IUq16cHjhLTvJ
u4FA33AGWWjCpTnA'
GUEST_TOKEN_PATH = Path('guest_token.txt')
INPUT_PATH = Path('unique_twitter_usernames.csv')
OUTPUT_PATH = Path('user_bios.csv')
MISSING_USERNAMES = Path('missing_usernames.txt')
NO_LEGACY = Path('no_legacy.txt')
HEADERS =
'"id","name","username","bio","url","join_datetime","join_date","join_time","tweets","location","following","followers","lik
es","media","private","verified","avatar","background_image"'

def _get_guest_token(attempts=3, max_iters=1e3) -> str:
  def thread_func(possible_keys: list) -> None:
      try:
          token = twint.token.Token(twint.config.Config())
          token.refresh()
          assert token.config.Guest_token
          possible_keys.append(token.config.Guest_token)
      except twint.token.RefreshTokenException as e:
          pass
  for _ in range(int(max_iters)):
      possible_keys = []
      threads: list[threading.Thread] = []
      for _ in range(attempts):
          thread = threading.Thread(target=thread_func, args=(possible_keys,))
          threads.append(thread)
          thread.start()
```

```
        for thread in threads:
            thread.join()
        if possible_keys:
            print(f'acquired_guest_token: {possible_keys[0]}')
            return possible_keys[0]
        time_to_wait = 3 + 27*random.random() # wait 3-30 seconds, randomly
        # print(f'No guest token. Waiting for {time_to_wait}')
        time.sleep(time_to_wait)
    raise ValueError('Something went wrong')

def get_guest_token() -> str:
    return GUEST_TOKEN_PATH.read_text() if GUEST_TOKEN_PATH.exists() else refresh_guest_token()

def refresh_guest_token() -> str:
    guest_token = _get_guest_token()
    GUEST_TOKEN_PATH.write_text(guest_token)
    return guest_token

def _lookup(username, guest_token):
    twint.run.Lookup(twint.config.Config(Username=username, Guest_token=guest_token, Pandas_au=True,
Pandas=True))
    record_new_users()

def record_new_users():
    from twint.storage.panda import User_df
    assert User_df is not None
    user_df_types = {'id': int, 'tweets': int, 'following': int, 'followers': int, 'likes': int, 'media': int, 'verified': bool, 'private':
bool}
    User_df.fillna(value={'tweets': 0, 'following': 0, 'followers': 0, 'likes': 0, 'media': 0}, inplace=True)
    User_df = User_df.astype(user_df_types)
    if not OUTPUT_PATH.exists():
        User_df.to_csv(OUTPUT_PATH, quoting=csv.QUOTE_NONNUMERIC, escapechar="\\", doublequote=False,
index=False)
    else:
        User_df.to_csv(OUTPUT_PATH, quoting=csv.QUOTE_NONNUMERIC, escapechar="\\", doublequote=False,
index=False, mode='a', header=False)

def lookup(*usernames):
    token = get_guest_token()
    for username in usernames:
        while True:
            try:
```

```
            _lookup(username, token)
        except ValueError as e:
            if str(e) == f'Cannot find twitter account with name = {username}':
                print(f'missing username: {username}')
                if not MISSING_USERNAMES.exists():
                    MISSING_USERNAMES.touch()
                names = set(MISSING_USERNAMES.read_text().splitlines())
                names.add(username)
                MISSING_USERNAMES.write_text('\n'.join(names))
            else:
                raise e
        except KeyError as e:
            if len(e.args) == 1 and e.args[0] == 'legacy':
                print(f'missing legacy: {username}')
                if not NO_LEGACY.exists():
                    NO_LEGACY.touch()
                names = set(NO_LEGACY.read_text().splitlines())
                names.add(username)
                NO_LEGACY.write_text('\n'.join(names))
            else:
                raise e
        except twint.token.TokenExpiryException:
            token = refresh_guest_token()
            continue
        break
def starting_usernames():
  usernames = {u.lower() for u in INPUT_PATH.read_text().splitlines()}
  if OUTPUT_PATH.exists():
     dtypes = {'id': int, 'tweets': int, 'following': int, 'followers': int, 'likes': int, 'media': int, 'verified': bool, 'private': bool}
     usernames = usernames - {u.lower() for u in pd.read_csv(OUTPUT_PATH, dtype=dtypes, escapechar="\\",
doublequote=False)['username']}
  if MISSING_USERNAMES.exists():
     usernames = usernames - {u.lower() for u in MISSING_USERNAMES.read_text().splitlines()}
  if NO_LEGACY.exists():
     usernames = usernames - {u.lower() for u in NO_LEGACY.read_text().splitlines()}
  yield from usernames

def lookup_all_users():
  usernames = list(starting_usernames())
  iteration = 0
  while usernames:
     iteration += 1
```

```
        start = time.time()
        lookup(*usernames[:min(10, len(usernames))])
        usernames = usernames[min(10, len(usernames)):]
        print(f'Iteration {iteration} took {time.time() - start}.')

def lookup_bio(username, token):
    twint.run.Lookup(twint.config.Config(Username=username, Guest_token=token, Pandas_au=True, Pandas=True))
    from twint.storage.panda import User_df
    assert User_df is not None
    User_df.fillna(value={'tweets': 0, 'following': 0, 'followers': 0, 'likes': 0, 'media': 0}, inplace=True)
    user_df_types = {'id': int, 'tweets': int, 'following': int, 'followers': int, 'likes': int, 'media': int, 'verified': bool, 'private':
bool}
    return User_df.astype(user_df_types).to_csv(quoting=csv.QUOTE_NONNUMERIC, escapechar="\\",
doublequote=False, index=False, header=False)

def worker(username_queue, bio_queue):
    guest_token = _get_guest_token()
    for username in username_queue:
        while True:
            try:
                bio_queue.put(lookup_bio(username, guest_token))
            except ValueError as e:
                if str(e) == f'Cannot find twitter account with name = {username}':
                    print(f'missing username: {username}')
                    with MISSING_USERNAMES.open('a') as f:
                        f.write(username + '\n')
                else:
                    raise e
            except KeyError as e:
                if len(e.args) == 1 and e.args[0] == 'legacy':
                    print(f'missing legacy: {username}')
                    with NO_LEGACY.open('a') as f:
                        f.write(username + '\n')
                else:
                    raise e
            except twint.token.TokenExpiryException:
                guest_token = _get_guest_token()
                continue
            break
    bio_queue.put(None)

def bio_writer(bio_queue, num_processes):
```

```
  num_terminators = 0
  while num_terminators < num_processes:
     bio = bio_queue.get()
     if bio is None:
        num_terminators += 1
        continue
     if not OUTPUT_PATH.exists():
        OUTPUT_PATH.write_text(HEADERS)
     with OUTPUT_PATH.open('a') as f:
        f.write(bio)
def main():
  NUMBER_OF_PROCESSES = 100
  bio_queue = multiprocessing.Queue()
  for username_queue in np.array_split(list(starting_usernames()), NUMBER_OF_PROCESSES):
     multiprocessing.Process(target=worker, args=(username_queue, bio_queue)).start()
  writer = multiprocessing.Process(target=bio_writer, args=(bio_queue, NUMBER_OF_PROCESSES))
  writer.start()
  writer.join()
if __name__ == '__main__':
  multiprocessing.freeze_support()
  main()
```

APPENDIX E - Code for Graphs & Statistical Data

```
import matplotlib.pyplot as plt
```

Figure E 1. Import Matplotlib into the Pandas data frame Google Colab workbook

```
df['year'] = df['date'].str.slice(stop=4)
```

Figure E 2. Separation of year and data to easily graph and manipulate data

```
IPython_default = plt.rcParams.copy()
```

Figure E 3. Inserting default parameters for the codebase

```
plt.style.use('seaborn-poster')
```

Figure E 4. Using the default 'seaborn-poster' styling for all graphs

```
SMALL_SIZE = 12
MEDIUM_SIZE = 16
BIGGER_SIZE = 20
plt.rc('font', size=MEDIUM_SIZE)          # controls default text sizes
plt.rc('axes', titlesize=SMALL_SIZE)     # fontsize of the axes title
plt.rc('axes', labelsize=SMALL_SIZE)    # fontsize of the x and y labels
plt.rc('xtick', labelsize=SMALL_SIZE)    # fontsize of the tick labels
plt.rc('ytick', labelsize=SMALL_SIZE)    # fontsize of the tick labels
plt.rc('legend', fontsize=SMALL_SIZE)    # legend fontsize
plt.rc('figure', titlesize=BIGGER_SIZE)  # fontsize of the figure title
```

Figure E 5. Setting size for different text styles for all graphs

```
fig, axes = plt.subplots(3, 5)
current_plot = 0
print('Year,N,Mean,Median,Standard Deviation, Skewness')
for year, year_df in df[['sentiment', 'year']][df['sentiment'] != 0].groupby('year'):
 ax = axes[current_plot // 5][current_plot % 5]
 year_df.hist(ax=ax, edgecolor='darkgrey', linewidth=0.5)
 print(
   f'{year},{len(year_df)},'
   f'{year_df.mean(numeric_only=True).sentiment:.3f},'
   f'{year_df.median(numeric_only=True).sentiment:.3f},'
   f'{year_df.std(numeric_only=True).sentiment:.3f},'
   f'{year_df.skew(numeric_only=True).sentiment:.3f}')
 ax.set_title(year)
 current_plot += 1
 ax.set_xlabel("Sentiment Score")
 ax.set_ylabel("Frequency of Sentiment")
 ax.set_axisbelow(True)
```

```
 ax.set_xlim((-1,1))
fig.savefig(
 '//content/gdrive/MyDrive/Colab Notebooks/sentiment_by_year.png',
 format='png',)
```

Figure E 6. Creating a graph and statistical analyses for sentiment of the dataset by year

```
fig, axes = plt.subplots(2,4)
current_plot = 0
print('stakeholder group,N,mean,median,standard deviation,skewness')
for category, category_df in df[['category', 'sentiment']][df['sentiment'] != 0].groupby('category'):
 ax = axes[current_plot // 4][current_plot % 4]
 category_df.hist(ax=ax, edgecolor='darkgrey', linewidth=0.5)
 ax.set_title(category)
 current_plot += 1
 ax.set_xlabel("Sentiment Score")
 ax.set_ylabel("Frequency of Sentiment")
 ax.set_axisbelow(True)
 ax.set_xlim((-1,1))
 print(
   f'{category},{len(category_df)},'
   f'{category_df.mean(numeric_only=True).sentiment:.3f},'
   f'{category_df.median(numeric_only=True).sentiment:.3f},'
   f'{category_df.std(numeric_only=True).sentiment:.3f},'
   f'{category_df.skew(numeric_only=True).sentiment:.3f}')
fig.savefig(
 '//content/gdrive/MyDrive/Colab Notebooks/sentiment_by_category.png',
 format='png',)
```

Figure E 7. Creating a graph and statistical analyses for sentiment of the dataset by stakeholder group

```
fig, ax = plt.subplots()
overall_df = df[['sentiment']][df['sentiment'] != 0]
overall_df.hist(ax=ax, edgecolor='darkgrey', linewidth=0.5)
ax.set_xlabel("Sentiment Score")
ax.set_ylabel("Frequency of Sentiment")
ax.set_title('')
ax.set_axisbelow(True)
ax.set_xlim((-1,1))
print(
 f'N = {len(overall_df)}, '
 f'mean = {overall_df.mean(numeric_only=True).sentiment:.3f}, '
 f'median = {overall_df.median(numeric_only=True).sentiment:.3f}, '
```

```
 f'stdev = {overall_df.std(numeric_only=True).sentiment:.3f}, '
 f'skewness = {overall_df.skew(numeric_only=True).sentiment:.3f}'
)
fig.savefig(
 '//content/gdrive/MyDrive/Colab Notebooks/overall_sentiment.png',
 format='png',)
```

Figure E 8. Creating a graph and statistical analyses for overall sentiment of the dataset

```
print('stakeholder group,year,N,mean,median,standard deviation, skewness')
for category_year, category_year_df in df[['category', 'sentiment', 'year']][df['sentiment'] !=
0].groupby(['category', 'year']):
 category, year = category_year
print(
   f'{category},{year},{len(category_year_df)},'
   f'{category_year_df.mean(numeric_only=True).sentiment:.3f},'
   f'{category_year_df.median(numeric_only=True).sentiment:.3f},'
   f'{category_year_df.std(numeric_only=True).sentiment:.3f},'
   f'{category_year_df.skew(numeric_only=True).sentiment:.3f}')
```

Figure E 9. Creating a table for the dataset to export to Excel

```
print('is canada,stakeholder group,year,N,mean,median,standard deviation,skewness')
for canada_category_year, canada_category_year_df in df[['is_canada', 'category', 'sentiment',
'year']][df['sentiment'] != 0].groupby(['is_canada', 'category', 'year']):
  canada, category, year = canada_category_year
  print(
    f'{canada},{category},{year},{len(canada_category_year_df)},'
    f'{canada_category_year_df.mean(numeric_only=True).sentiment:.3f},'
    f'{canada_category_year_df.median(numeric_only=True).sentiment:.3f},'
    f'{canada_category_year_df.std(numeric_only=True).sentiment:.3f},'
    f'{canada_category_year_df.skew(numeric_only=True).sentiment:.3f}'
  )
```

Figure E 10. Creating a table for the Canada and International stakeholder group by year dataset to export to Excel

```
print('is canada,year,N,mean,median,standard deviation,skewness')
for canada_year, canada_year_df in df[['is_canada', 'sentiment', 'year']][df['sentiment'] !=
0].groupby(['is_canada', 'year']):
  canada, year = canada_year
  print(
    f'{canada},{year},{len(canada_year_df)},'
    f'{canada_year_df.mean(numeric_only=True).sentiment:.3f},'
    f'{canada_year_df.median(numeric_only=True).sentiment:.3f},'
    f'{canada_year_df.std(numeric_only=True).sentiment:.3f},'
    f'{canada_year_df.skew(numeric_only=True).sentiment:.3f}'
  )
```

Figure E 11. Creating a table for the Canada and International by year dataset to export to Excel

```
print('is canada,stakeholder group,N,mean,median,standard deviation,skewness')
for canada_category, canada_category_df in df[['is_canada', 'category', 'sentiment']][df['sentiment'] !=
0].groupby(['is_canada', 'category']):
  canada, category = canada_category
  print(
    f'{canada},{category},{len(canada_category_df)},'
    f'{canada_category_df.mean(numeric_only=True).sentiment:.3f},'
    f'{canada_category_df.median(numeric_only=True).sentiment:.3f},'
    f'{canada_category_df.std(numeric_only=True).sentiment:.3f},'
    f'{canada_category_df.skew(numeric_only=True).sentiment:.3f}'
  )
```

Figure E 12. Creating a table for the Canada and International stakeholder group dataset to export to Excel

```
print('is canada,N,mean,median,standard deviation,skewness')
for canada, canada_df in df[['is_canada', 'sentiment']][df['sentiment'] != 0].groupby(['is_canada']):
  print(
    f'{canada},{len(canada_df)},'
    f'{canada_df.mean(numeric_only=True).sentiment:.3f},'
    f'{canada_df.median(numeric_only=True).sentiment:.3f},'
    f'{canada_df.std(numeric_only=True).sentiment:.3f},'
    f'{canada_df.skew(numeric_only=True).sentiment:.3f}'
  )
```

Figure E 13. Creating a table for the Canada and International dataset to export to Excel

```
fig, axes = plt.subplots(1, 2)
current_plot = 0
for canada, canada_df in df[['is_canada', 'sentiment']][df['sentiment'] != 0].groupby(['is_canada']):
  ax = axes[current_plot]
  canada_df.hist(ax=ax, edgecolor='darkgrey', linewidth=0.5)
  ax.set_title(f'{"Canada" if canada else "International (Excluding Canada)"}')
  current_plot += 1
  ax.set_xlabel("Sentiment Score")
  ax.set_ylabel("Frequency of Sentiment")
  ax.set_axisbelow(True)
  ax.set_xlim((-1,1))
fig.savefig(
  'drive/MyDrive/Colab Notebooks/sentiment_by_canada_overall.png',
  format='png',
)
```

Figure E 14. Creating a graph for Canada and International dataset

```
fig, axes = plt.subplots(4, 4)
current_plot = 0
for canada_category, canada_category_df in df[['is_canada', 'category', 'sentiment']][df['sentiment'] !=
0].groupby(['is_canada', 'category']):
  canada, category = canada_category
  ax = axes[current_plot // 4][current_plot % 4]
  canada_category_df.hist(ax=ax, edgecolor='darkgrey', linewidth=0.5)
  ax.set_title(f'{"Canada" if canada else "International"}\n{category}')
  current_plot += 1
  ax.set_xlabel("Sentiment Score")
  ax.set_ylabel("Frequency")
  ax.set_axisbelow(True)
  ax.set_xlim((-1,1))
fig.tight_layout()
fig.savefig(
  'drive/MyDrive/Colab Notebooks/sentiment_by_canada_category.png',
  format='png',
)
```

Figure E 15. Creating a graph for Canada and International by stakeholder group

```
fig, axes = plt.subplots(4, 4)
current_plot = 0
for year, year_df in df[df.is_canada][['year', 'sentiment']][df['sentiment'] != 0].groupby(['year']):
  ax = axes[current_plot // 4][current_plot % 4]
  year_df.hist(ax=ax, edgecolor='darkgrey', linewidth=0.5)
  ax.set_title(f'Canada {year}')
  current_plot += 1
  ax.set_xlabel("Sentiment Score")
  ax.set_ylabel("Frequency")
  ax.set_axisbelow(True)
  ax.set_xlim((-1,1))
fig.tight_layout()

fig.savefig(
  'drive/MyDrive/Colab Notebooks/sentiment_by_is_canada_year.png',
  format='png',
)
```

Figure E 16. Creating a graph for Canada by year

```
fig, axes = plt.subplots(4, 4)
current_plot = 0
for year, year_df in df[~df.is_canada][['year', 'sentiment']][df['sentiment'] != 0].groupby(['year']):
  ax = axes[current_plot // 4][current_plot % 4]
  year_df.hist(ax=ax, edgecolor='darkgrey', linewidth=0.5)
  ax.set_title(f'International (Excluding Canada)\n{year}')
  current_plot += 1
  ax.set_xlabel("Sentiment Score")
  ax.set_ylabel("Frequency")
  ax.set_axisbelow(True)
  ax.set_xlim((-1,1))
fig.tight_layout()
fig.savefig(
  'drive/MyDrive/Colab Notebooks/sentiment_by_is_international_year.png',
  format='png',
)
```

Figure E 17. Creating a graph for International by year

APPENDIX F – Definitions

Aquaculture

“A catchall term for the farming of aquatic species and plants for harvest (Young et. al., 2019).

Citizen Engagement

“Governments and citizens/groups undertake a process of “deliberative dialogue” by which participants commit to a process that seeks a public interest solution, including the possibility of debating current government assumptions/policies and the advocacy interests of others.” (Department of Fisheries and Oceans, 2004).

Consultation

“A two-way process that seeks direct participation from the public or specific stakeholders on a range of issues to inform government decisions about policies, programs, services, and legislative and regulatory initiatives, whether in person or online (Treasury Board, 2019). The Privy Council Office describes consultation as “an interactive process seeking direct participation from Canadians.” Fisheries and Oceans Canada, Pacific Region, undertakes consultations to improve departmental decision-making processes, promote understanding of fisheries, oceans, and marine transport issues, and strengthen relationships. Policy guidance and strategic direction for public consultation activity is provided by the Consultation Secretariat in the Policy Branch” (Treasury Board, 2019).

“Conventional” Consultation

“Government requests feedback in a decision-making process after having determined the problem or issue and having identified the participants in the process and makes the final decision” (Department of Fisheries and Oceans, 2004).

Environmental justice

“The obligation of non-discrimination in environmental protection” (Boyd, 2016).

Environmental injustice

“The environmental benefits and burdens that have a significant and disproportionate negative impact on vulnerable or marginalized groups.”

Finfish

“A bony fish, such as a salmon, or a cartilaginous fish, such as a shark, especially in contrast to a shellfish or other aquatic animal (Oxford Dictionary).

First Nations peoples

“Any of the groups of Indigenous peoples of Canada officially recognized as an administrative unit by the federal government or functioning as such without official status (Oxford Dictionary). The term is generally understood to exclude the Inuit and Metis.

Governance Framework

“A new strategy of governing that brings multiple stakeholders together in common forums with public agencies to engage in consensus-oriented decision making.” (Ansell, 2008).

“A governing arrangement where one or more public agencies directly engage non-state stakeholders in a collective decision-making process that is formal, consensus-oriented, and deliberative and that aims to make or implement public policy or manage public programs or assets.” (Ansell, 2008).

Indigenous Knowledge

defined as “the *local knowledge** held by Indigenous peoples or local knowledge unique to a given culture or society.” (Berkes, 2018, pg. 9)

*“*local knowledge* is used when referring to recent knowledge” (Berkes, 2018, pg. 9)

Knowledge of the Land

In the Canadian North, aboriginal peoples often refer to their "knowledge of the land" rather than to ecological knowledge. *Land* to them, however, is more than the physical landscape; it includes the living environment. (Berkes, 2018, pg. 5)

Vulnerable populations of Canadians

“Indigenous peoples, African Canadians, children, recent immigrants, migrant workers, individuals with compromised immune systems or environmental sensitivities, and people experiencing social and economic disadvantages such as poverty and homelessness” (Boyd, 2016).

APPENDIX G – Additional Tables

Table G 1. Mean, median, standard deviation and skewness of each stakeholder group from 2007 to 2021*

Stakeholder Group	Year	N	Mean	Median	Standard Deviation	Skewness
A. Academic / Researcher	2008	16	0.227	0.307	0.432	-0.629
	2009	334	0.249	0.382	0.402	-0.778
	2010	699	0.318	0.402	0.357	-1.291
	2011	2,042	0.249	0.318	0.37	-1.041
	2012	2,863	0.286	0.361	0.372	-1.006
	2013	3,150	0.247	0.361	0.404	-0.805
	2014	4,058	0.299	0.382	0.371	-1.008
	2015	4,439	0.298	0.4	0.389	-1.014
	2016	4,994	0.34	0.421	0.359	-1.176
	2017	6,173	0.338	0.421	0.383	-1.041
	2018	9,069	0.387	0.457	0.406	-1.029
	2019	9,966	0.38	0.459	0.424	-1.072
	2020	10,414	0.381	0.457	0.416	-0.952
	2021	6,642	0.397	0.491	0.421	-1.08
B. Industry / Worker	2007	14	0.017	0.21	0.612	-0.149
	2008	58	0.293	0.393	0.364	-1.087
	2009	1,211	0.267	0.382	0.395	-0.858
	2010	3,641	0.301	0.402	0.379	-0.994
	2011	7,591	0.233	0.382	0.428	-0.78
	2012	9,582	0.256	0.382	0.407	-0.829
	2013	10,538	0.257	0.379	0.405	-0.873
	2014	10,181	0.303	0.402	0.373	-1.011
	2015	11,489	0.307	0.382	0.369	-1.08

	2016	15,089	0.302	0.402	0.374	-1.09
	2017	13,408	0.347	0.402	0.37	-1.09
	2018	20,457	0.377	0.459	0.413	-1.097
	2019	23,937	0.393	0.475	0.408	-1.128
	2020	25,047	0.362	0.459	0.434	-1.118
	2021	15,452	0.375	0.459	0.423	-1.098
C. ENGO / Conservation	2008	12	0.122	0.262	0.369	-0.36
	2009	119	0.133	0.25	0.388	-0.6
	2010	301	0.249	0.361	0.385	-0.952
	2011	560	0.253	0.318	0.368	-0.886
	2012	671	0.307	0.382	0.354	-1.049
	2013	1,061	0.27	0.271	0.333	-0.999
	2014	729	0.296	0.402	0.364	-1.007
	2015	902	0.286	0.402	0.393	-1.051
	2016	1,201	0.323	0.402	0.353	-1.178
	2017	1,509	0.305	0.402	0.385	-1.091
	2018	2,312	0.344	0.44	0.423	-1.063
	2019	2,209	0.348	0.436	0.435	-1.047
	2020	4,020	0.226	0.361	0.447	-0.804
	2021	1,348	0.33	0.408	0.444	-0.876
D. Government	2008	4	0.17	0.295	0.283	-1.871
	2009	29	0.229	0.318	0.402	-0.598
	2010	92	0.342	0.402	0.391	-0.698
	2011	220	0.147	0.296	0.4	-0.614
	2012	176	0.219	0.361	0.385	-0.626
	2013	211	0.331	0.402	0.352	-1.068

	2014	217	0.308	0.4	0.356	-0.985
	2015	226	0.278	0.382	0.389	-1.033
	2016	240	0.4	0.44	0.33	-1.125
	2017	315	0.342	0.402	0.36	-1.125
	2018	320	0.371	0.421	0.384	-1.061
	2019	527	0.239	0.382	0.48	-0.617
	2020	527	0.213	0.361	0.457	-0.474
	2021	320	0.16	0.299	0.515	-0.312
E. Indigenous	2009	1	0.542	0.542	**N/A	N/A
	2010	1	0.296	0.296	N/A	N/A
	2011	7	0.514	0.527	0.189	-0.32
	2012	3	0.276	0.611	0.604	-1.729
	2013	5	0.137	0.318	0.447	-1.459
	2014	7	0.036	0.153	0.401	-0.082
	2015	6	0.415	0.526	0.467	-1.756
	2016	6	0.278	0.345	0.38	-0.6
	2017	10	0.269	0.438	0.482	-0.679
	2018	45	0.348	0.477	0.487	-0.887
	2019	19	0.349	0.493	0.447	-1.134
	2020	17	0.508	0.493	0.332	-0.522
	2021	21	0.287	0.512	0.528	-0.678
F. Media	2008	13	0.314	0.34	0.314	-2.46
	2009	103	0.277	0.382	0.365	-1.083
	2010	191	0.326	0.402	0.361	-1.093
	2011	286	0.188	0.339	0.407	-0.712
	2012	583	0.224	0.273	0.34	-0.796

	2013	463	0.249	0.34	0.399	-0.81
	2014	457	0.347	0.402	0.356	-1.092
	2015	498	0.229	0.382	0.431	-0.869
	2016	487	0.241	0.382	0.411	-0.88
	2017	407	0.179	0.318	0.389	-0.489
	2018	586	0.243	0.382	0.451	-0.766
	2019	529	0.224	0.361	0.451	-0.791
	2020	512	0.272	0.382	0.44	-0.825
	2021	377	0.227	0.382	0.475	-0.767
G. Other	2008	4	0.076	0.158	0.591	-0.453
	2009	59	0.07	0.226	0.45	-0.314
	2010	254	0.299	0.421	0.35	-1.168
	2011	409	0.246	0.402	0.445	-0.889
	2012	555	0.257	0.382	0.408	-0.795
	2013	666	0.286	0.421	0.43	-0.806
	2014	794	0.311	0.402	0.362	-1.15
	2015	768	0.291	0.382	0.377	-1.108
	2016	688	0.324	0.421	0.381	-1.282
	2017	569	0.303	0.382	0.365	-0.959
	2018	756	0.317	0.421	0.437	-0.989
	2019	923	0.268	0.402	0.463	-0.749
	2020	1,108	0.122	0.318	0.548	-0.493
	2021	663	0.225	0.382	0.489	-0.67
H. No Category	2008	4	0.018	0.21	0.484	-1.727
	2009	68	0.264	0.382	0.383	-1.19
	2010	199	0.284	0.402	0.385	-0.944

	2011	399	0.237	0.382	0.457	-0.801
	2012	687	0.27	0.382	0.415	-0.999
	2013	651	0.24	0.382	0.435	-0.76
	2014	490	0.317	0.421	0.41	-1.033
	2015	581	0.281	0.382	0.369	-1.163
	2016	457	0.269	0.382	0.395	-1.035
	2017	504	0.236	0.382	0.44	-0.731
	2018	528	0.288	0.421	0.462	-0.878
	2019	582	0.275	0.382	0.452	-0.818
	2020	826	0.182	0.382	0.546	-0.626
	2021	555	0.259	0.402	0.484	-0.771

*Note: If the table is missing a year within the stakeholder group, that means there is no data within the specific year that falls into that stakeholder group category.
**Note: N/A means there is no calculation from the data (i.e., there isn't enough data)

Table G 2. Mean, median, standard deviation and skewness of International and Canada datasets for each stakeholder group from 2007 to 2021*

Is Canada	Stakeholder Group	Year	N	Mean	Median	Standard Deviation	Skewness
International	A. Academic / Researcher	2008	16	0.227	0.307	0.432	-0.629
International	A. Academic / Researcher	2009	326	0.246	0.382	0.401	-0.767
International	A. Academic / Researcher	2010	696	0.318	0.402	0.356	-1.298
International	A. Academic / Researcher	2011	2036	0.25	0.318	0.368	-1.046
International	A. Academic / Researcher	2012	2842	0.286	0.361	0.372	-1.002
International	A. Academic / Researcher	2013	3120	0.247	0.361	0.404	-0.805
International	A. Academic / Researcher	2014	4006	0.298	0.382	0.371	-1.012
International	A. Academic / Researcher	2015	4354	0.3	0.4	0.386	-1.023
International	A. Academic / Researcher	2016	4930	0.343	0.421	0.356	-1.183
International	A. Academic / Researcher	2017	6104	0.339	0.421	0.382	-1.045

International	A. Academic / Researcher	2018	8964	0.388	0.457	0.405	-1.031
International	A. Academic / Researcher	2019	9854	0.38	0.459	0.423	-1.074
International	A. Academic / Researcher	2020	10323	0.381	0.457	0.415	-0.95
International	A. Academic / Researcher	2021	6566	0.398	0.493	0.42	-1.08
International	B. Industry / Worker	2007	14	0.017	0.21	0.612	-0.149
International	B. Industry / Worker	2008	57	0.288	0.385	0.364	-1.066
International	B. Industry / Worker	2009	1186	0.269	0.382	0.392	-0.854
International	B. Industry / Worker	2010	3552	0.305	0.402	0.377	-1.012
International	B. Industry / Worker	2011	7457	0.233	0.382	0.427	-0.783
International	B. Industry / Worker	2012	9378	0.259	0.382	0.405	-0.842
International	B. Industry / Worker	2013	10359	0.258	0.38	0.404	-0.877
International	B. Industry / Worker	2014	9994	0.304	0.402	0.373	-1.019
International	B. Industry / Worker	2015	11309	0.309	0.382	0.367	-1.081
International	B. Industry / Worker	2016	14923	0.302	0.402	0.374	-1.09
International	B. Industry / Worker	2017	13230	0.347	0.418	0.37	-1.092
International	B. Industry / Worker	2018	20167	0.378	0.459	0.412	-1.104
International	B. Industry / Worker	2019	23667	0.393	0.475	0.408	-1.127
International	B. Industry / Worker	2020	24859	0.362	0.459	0.434	-1.118
International	B. Industry / Worker	2021	15303	0.374	0.459	0.423	-1.097
International	C. ENGO / Conservation	2008	12	0.122	0.262	0.369	-0.36
International	C. ENGO / Conservation	2009	119	0.133	0.25	0.388	-0.6
International	C. ENGO / Conservation	2010	299	0.253	0.361	0.383	-0.967
International	C. ENGO / Conservation	2011	555	0.252	0.318	0.369	-0.884
International	C. ENGO / Conservation	2012	647	0.301	0.382	0.35	-1.057
International	C. ENGO / Conservation	2013	1048	0.27	0.271	0.331	-1.003
International	C. ENGO / Conservation	2014	719	0.296	0.402	0.364	-1.005
International	C. ENGO / Conservation	2015	893	0.29	0.402	0.391	-1.063
International	C. ENGO / Conservation	2016	1195	0.324	0.402	0.352	-1.179
International	C. ENGO / Conservation	2017	1505	0.305	0.402	0.385	-1.09
International	C. ENGO / Conservation	2018	2310	0.344	0.44	0.423	-1.063
International	C. ENGO / Conservation	2019	2201	0.349	0.436	0.435	-1.048
International	C. ENGO / Conservation	2020	3989	0.23	0.361	0.443	-0.807
International	C. ENGO / Conservation	2021	1336	0.332	0.419	0.444	-0.88
International	D. Government	2008	4	0.17	0.295	0.283	-1.871
International	D. Government	2009	29	0.229	0.318	0.402	-0.598
International	D. Government	2010	92	0.342	0.402	0.391	-0.698
International	D. Government	2011	218	0.144	0.296	0.4	-0.603

International	D. Government	2012	175	0.218	0.361	0.386	-0.621
International	D. Government	2013	206	0.332	0.402	0.35	-1.057
International	D. Government	2014	216	0.31	0.401	0.356	-1.002
International	D. Government	2015	225	0.277	0.382	0.39	-1.03
International	D. Government	2016	240	0.4	0.44	0.33	-1.125
International	D. Government	2017	310	0.342	0.402	0.363	-1.122
International	D. Government	2018	316	0.371	0.421	0.384	-1.068
International	D. Government	2019	502	0.24	0.382	0.479	-0.608
International	D. Government	2020	525	0.214	0.361	0.457	-0.475
International	D. Government	2021	316	0.164	0.299	0.514	-0.314
International	E. Indigenous	2009	1	0.542	0.542	**N/A	N/A
International	E. Indigenous	2010	1	0.296	0.296	N/A	N/A
International	E. Indigenous	2011	7	0.514	0.527	0.189	-0.32
International	E. Indigenous	2012	3	0.276	0.611	0.604	-1.729
International	E. Indigenous	2013	5	0.137	0.318	0.447	-1.459
International	E. Indigenous	2014	7	0.036	0.153	0.401	-0.082
International	E. Indigenous	2015	6	0.415	0.526	0.467	-1.756
International	E. Indigenous	2016	6	0.278	0.345	0.38	-0.6
International	E. Indigenous	2017	10	0.269	0.438	0.482	-0.679
International	E. Indigenous	2018	44	0.334	0.477	0.483	-0.889
International	E. Indigenous	2019	18	0.346	0.493	0.459	-1.089
International	E. Indigenous	2020	17	0.508	0.493	0.332	-0.522
International	E. Indigenous	2021	21	0.287	0.512	0.528	-0.678
International	F. Media	2008	13	0.314	0.34	0.314	-2.46
International	F. Media	2009	100	0.271	0.382	0.364	-1.117
International	F. Media	2010	189	0.329	0.402	0.36	-1.114
International	F. Media	2011	275	0.192	0.34	0.402	-0.718
International	F. Media	2012	580	0.224	0.273	0.34	-0.798
International	F. Media	2013	458	0.252	0.34	0.396	-0.823
International	F. Media	2014	450	0.352	0.402	0.352	-1.113
International	F. Media	2015	486	0.232	0.382	0.427	-0.873
International	F. Media	2016	483	0.242	0.382	0.411	-0.877
International	F. Media	2017	402	0.181	0.318	0.389	-0.496
International	F. Media	2018	584	0.244	0.382	0.451	-0.771
International	F. Media	2019	525	0.222	0.361	0.452	-0.783
International	F. Media	2020	505	0.275	0.402	0.44	-0.826
International	F. Media	2021	375	0.228	0.382	0.474	-0.771
International	G. Other	2008	4	0.076	0.158	0.591	-0.453
International	G. Other	2009	56	0.069	0.226	0.451	-0.294

International	G. Other	2010	252	0.299	0.421	0.351	-1.162
International	G. Other	2011	407	0.246	0.402	0.446	-0.892
International	G. Other	2012	554	0.256	0.382	0.408	-0.793
International	G. Other	2013	661	0.289	0.421	0.428	-0.812
International	G. Other	2014	783	0.313	0.402	0.362	-1.161
International	G. Other	2015	757	0.288	0.382	0.379	-1.095
International	G. Other	2016	685	0.324	0.421	0.382	-1.282
International	G. Other	2017	562	0.305	0.382	0.363	-0.954
International	G. Other	2018	754	0.316	0.421	0.437	-0.987
International	G. Other	2019	917	0.268	0.402	0.462	-0.754
International	G. Other	2020	1105	0.12	0.318	0.548	-0.49
International	G. Other	2021	660	0.226	0.382	0.489	-0.669
International	H. No Category	2008	4	0.018	0.21	0.484	-1.727
International	H. No Category	2009	67	0.261	0.382	0.385	-1.167
International	H. No Category	2010	198	0.283	0.392	0.386	-0.937
International	H. No Category	2011	399	0.237	0.382	0.457	-0.801
International	H. No Category	2012	678	0.271	0.382	0.414	-1.011
International	H. No Category	2013	645	0.238	0.382	0.436	-0.757
International	H. No Category	2014	477	0.321	0.421	0.411	-1.055
International	H. No Category	2015	543	0.283	0.382	0.378	-1.148
International	H. No Category	2016	447	0.268	0.382	0.397	-1.022
International	H. No Category	2017	496	0.236	0.382	0.442	-0.724
International	H. No Category	2018	517	0.287	0.421	0.46	-0.875
International	H. No Category	2019	576	0.275	0.382	0.451	-0.826
International	H. No Category	2020	822	0.181	0.382	0.546	-0.62
International	H. No Category	2021	551	0.259	0.402	0.485	-0.769
Canada	A. Academic / Researcher	2009	8	0.36	0.392	0.431	-1.69
Canada	A. Academic / Researcher	2010	3	0.228	0.382	0.642	-1.018
Canada	A. Academic / Researcher	2011	6	-0.263	-0.295	0.607	1.385
Canada	A. Academic / Researcher	2012	21	0.286	0.382	0.354	-1.808
Canada	A. Academic / Researcher	2013	30	0.187	0.318	0.411	-0.875
Canada	A. Academic / Researcher	2014	52	0.311	0.44	0.421	-0.802
Canada	A. Academic / Researcher	2015	85	0.203	0.402	0.505	-0.543
Canada	A. Academic / Researcher	2016	64	0.127	0.317	0.486	-0.457

Canada	A. Academic / Researcher	2017	69	0.219	0.361	0.453	-0.66
Canada	A. Academic / Researcher	2018	105	0.339	0.402	0.452	-0.83
Canada	A. Academic / Researcher	2019	112	0.363	0.494	0.53	-0.892
Canada	A. Academic / Researcher	2020	91	0.428	0.542	0.479	-1.219
Canada	A. Academic / Researcher	2021	76	0.365	0.477	0.496	-1.037
Canada	B. Industry / Worker	2008	1	0.612	0.612	N/A	N/A
Canada	B. Industry / Worker	2009	25	0.141	0.382	0.483	-0.77
Canada	B. Industry / Worker	2010	89	0.147	0.318	0.431	-0.369
Canada	B. Industry / Worker	2011	134	0.209	0.371	0.458	-0.623
Canada	B. Industry / Worker	2012	204	0.098	0.3	0.471	-0.258
Canada	B. Industry / Worker	2013	179	0.169	0.325	0.446	-0.632
Canada	B. Industry / Worker	2014	187	0.229	0.382	0.396	-0.641
Canada	B. Industry / Worker	2015	180	0.228	0.328	0.443	-0.884
Canada	B. Industry / Worker	2016	166	0.293	0.361	0.381	-1.087
Canada	B. Industry / Worker	2017	178	0.316	0.382	0.322	-0.987
Canada	B. Industry / Worker	2018	290	0.297	0.381	0.464	-0.648
Canada	B. Industry / Worker	2019	270	0.392	0.467	0.45	-1.192
Canada	B. Industry / Worker	2020	188	0.349	0.458	0.491	-1.023
Canada	B. Industry / Worker	2021	149	0.457	0.539	0.429	-1.24
Canada	C. ENGO / Conservation	2010	2	-0.326	-0.326	0.387	N/A
Canada	C. ENGO / Conservation	2011	5	0.361	0.382	0.251	0.747
Canada	C. ENGO / Conservation	2012	24	0.455	0.601	0.433	-1.52
Canada	C. ENGO / Conservation	2013	13	0.246	0.382	0.481	-0.775
Canada	C. ENGO / Conservation	2014	10	0.332	0.431	0.332	-1.258
Canada	C. ENGO / Conservation	2015	9	-0.048	0.25	0.441	-0.349
Canada	C. ENGO / Conservation	2016	6	0.131	0.259	0.53	-0.813
Canada	C. ENGO / Conservation	2017	4	0.617	0.689	0.204	-1.709
Canada	C. ENGO / Conservation	2018	2	0.684	0.684	0.247	N/A
Canada	C. ENGO / Conservation	2019	8	0.238	0.33	0.379	-1.232
Canada	C. ENGO / Conservation	2020	31	-0.238	-0.418	0.63	0.444
Canada	C. ENGO / Conservation	2021	12	0.1	0.284	0.406	-1.185
Canada	D. Government	2011	2	0.519	0.519	0.166	N/A
Canada	D. Government	2012	1	0.318	0.318	N/A	N/A
Canada	D. Government	2013	5	0.281	0.368	0.448	-1.875
Canada	D. Government	2014	1	-0.153	-0.153	N/A	N/A
Canada	D. Government	2015	1	0.318	0.318	N/A	N/A

Canada	D. Government	2017	5	0.332	0.296	0.152	0.737
Canada	D. Government	2018	4	0.355	0.394	0.379	-0.397
Canada	D. Government	2019	25	0.206	0.296	0.514	-0.808
Canada	D. Government	2020	2	0.007	0.007	0.819	N/A
Canada	D. Government	2021	4	-0.167	-0.139	0.61	-0.03
Canada	E. Indigenous	2018	1	0.965	0.965	N/A	N/A
Canada	E. Indigenous	2019	1	0.402	0.402	N/A	N/A
Canada	F. Media	2009	3	0.479	0.421	0.384	0.663
Canada	F. Media	2010	2	0	0	0.45	N/A
Canada	F. Media	2011	11	0.094	0.202	0.535	-0.482
Canada	F. Media	2012	3	0.127	0.318	0.367	-1.707
Canada	F. Media	2013	5	-0.019	-0.296	0.579	0.472
Canada	F. Media	2014	7	0.031	-0.226	0.517	0.284
Canada	F. Media	2015	12	0.092	0.371	0.564	-0.576
Canada	F. Media	2016	4	0.152	0.382	0.512	-1.946
Canada	F. Media	2017	5	0.058	0.077	0.382	-0.098
Canada	F. Media	2018	2	-0.076	-0.076	0.461	N/A
Canada	F. Media	2019	4	0.443	0.37	0.183	1.794
Canada	F. Media	2020	7	0.052	0.273	0.457	-1.377
Canada	F. Media	2021	2	0	0	0.933	N/A
Canada	G. Other	2009	3	0.086	0.382	0.53	-1.729
Canada	G. Other	2010	2	0.324	0.324	0.04	N/A
Canada	G. Other	2011	2	0.117	0.117	0.346	N/A
Canada	G. Other	2012	1	0.71	0.71	N/A	N/A
Canada	G. Other	2013	5	-0.111	-0.281	0.581	0.399
Canada	G. Other	2014	11	0.176	0.077	0.338	-0.673
Canada	G. Other	2015	11	0.494	0.421	0.168	0.267
Canada	G. Other	2016	3	0.271	0.359	0.191	-1.637
Canada	G. Other	2017	7	0.09	0.318	0.494	-0.964
Canada	G. Other	2018	2	0.494	0.494	0.344	N/A
Canada	G. Other	2019	6	0.206	0.317	0.588	-0.237
Canada	G. Other	2020	3	0.576	0.784	0.366	-1.732
Canada	G. Other	2021	3	-0.022	0.273	0.662	-1.608
Canada	H. No Category	2009	1	0.475	0.475	N/A	N/A
Canada	H. No Category	2010	1	0.44	0.44	N/A	N/A
Canada	H. No Category	2012	9	0.171	0.172	0.52	-0.324
Canada	H. No Category	2013	6	0.373	0.382	0.33	-0.601
Canada	H. No Category	2014	13	0.161	0.296	0.341	-0.594
Canada	H. No Category	2015	38	0.254	0.318	0.224	-2.038

Canada	H. No Category	2016	10	0.32	0.35	0.274	-2.247
Canada	H. No Category	2017	8	0.267	0.318	0.352	-1.638
Canada	H. No Category	2018	11	0.35	0.586	0.578	-1.211
Canada	H. No Category	2019	6	0.306	0.397	0.594	-0.586
Canada	H. No Category	2020	4	0.563	0.555	0.245	0.149
Canada	H. No Category	2021	4	0.263	0.361	0.21	-1.986

*Note: If the table is missing a year within the stakeholder group, that means there is no data within the specific year that falls into that stakeholder group category.
**Note: N/A means there is no calculation from the data (i.e., there isn't enough data)

APPENDIX H - Graphs

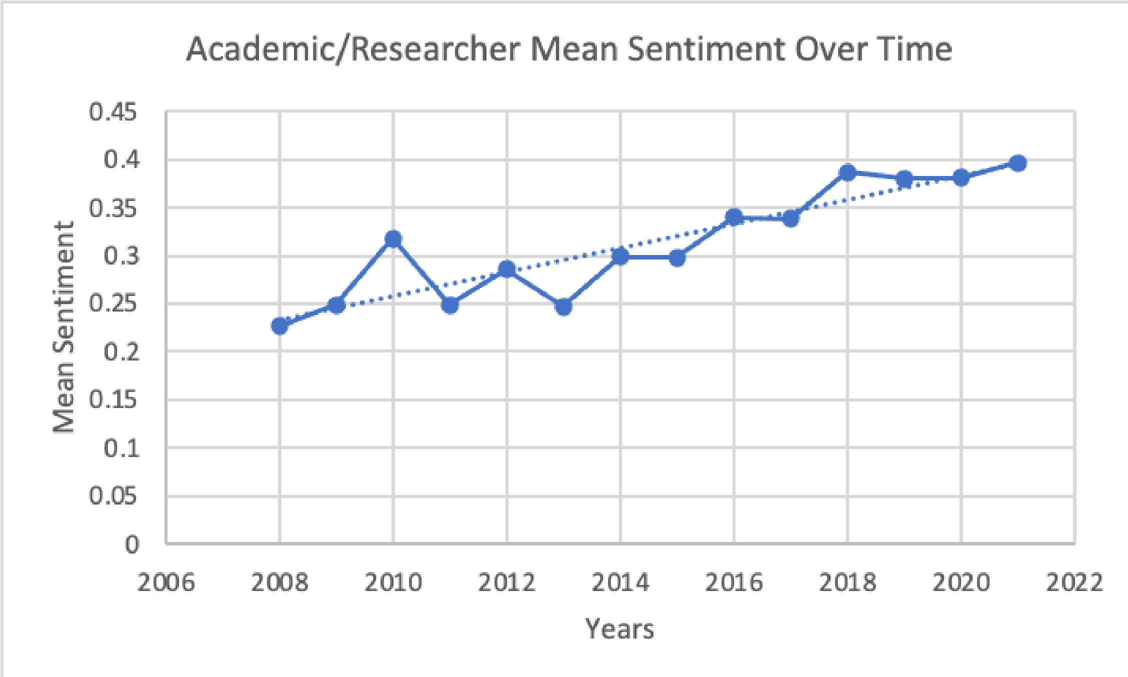

Figure H 1. Academic/Researcher mean sentiment over time

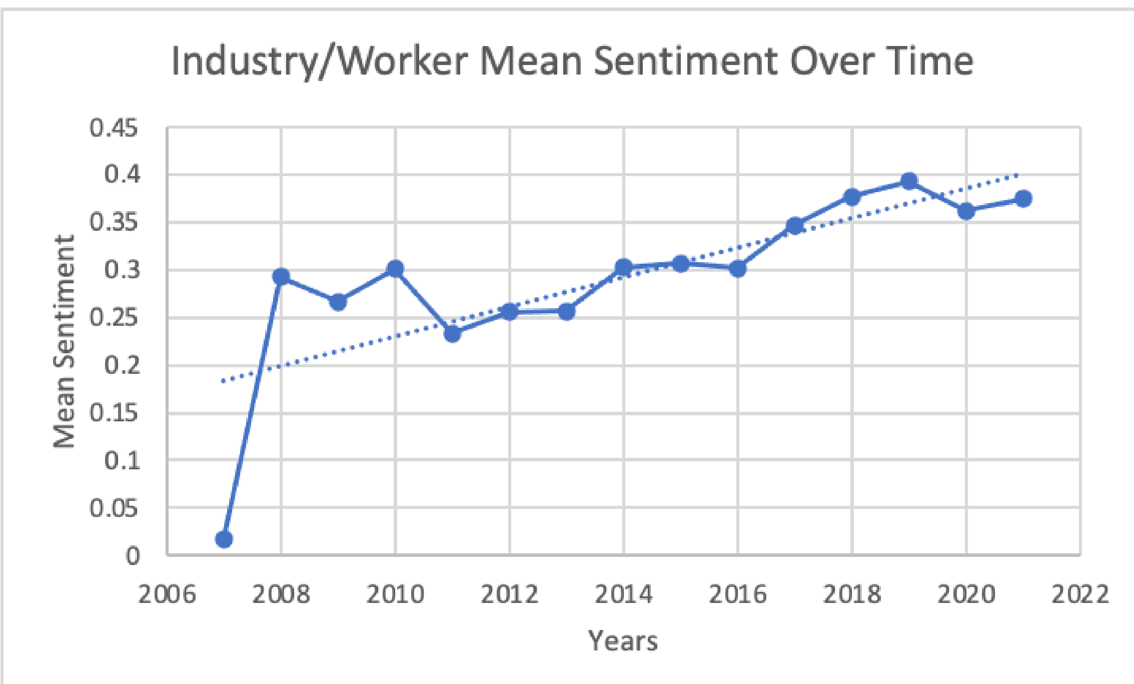

Figure H 2. Industry/Worker mean sentiment over time

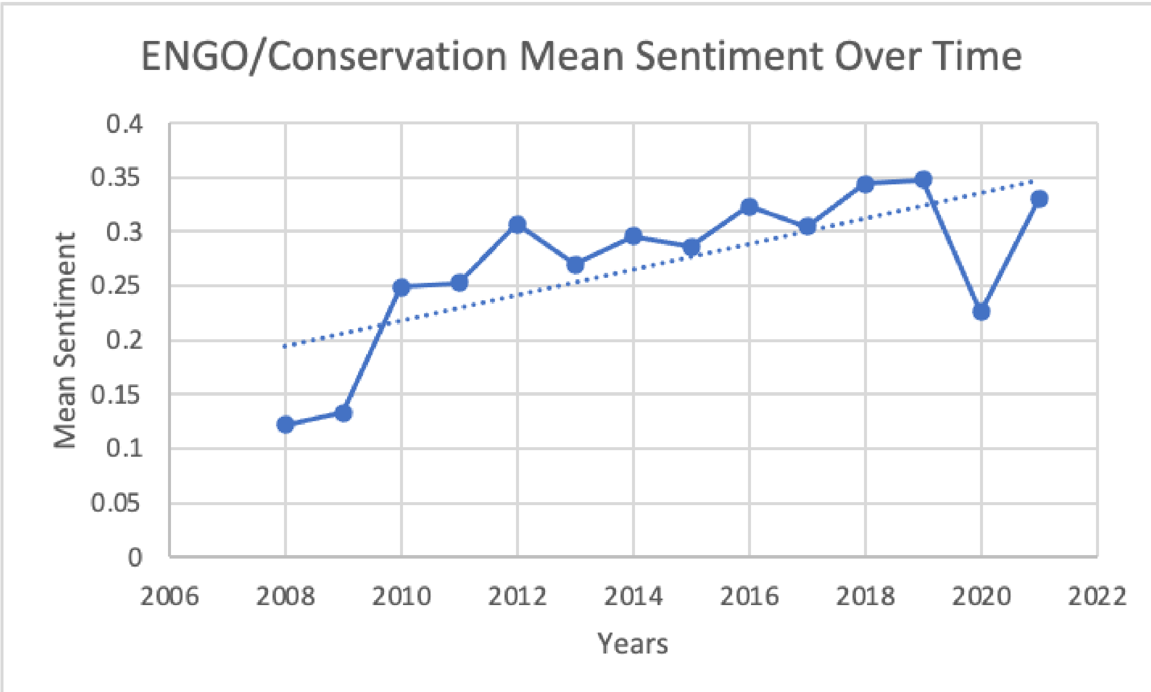

Figure H 3. ENGO/Conservation mean sentiment over time

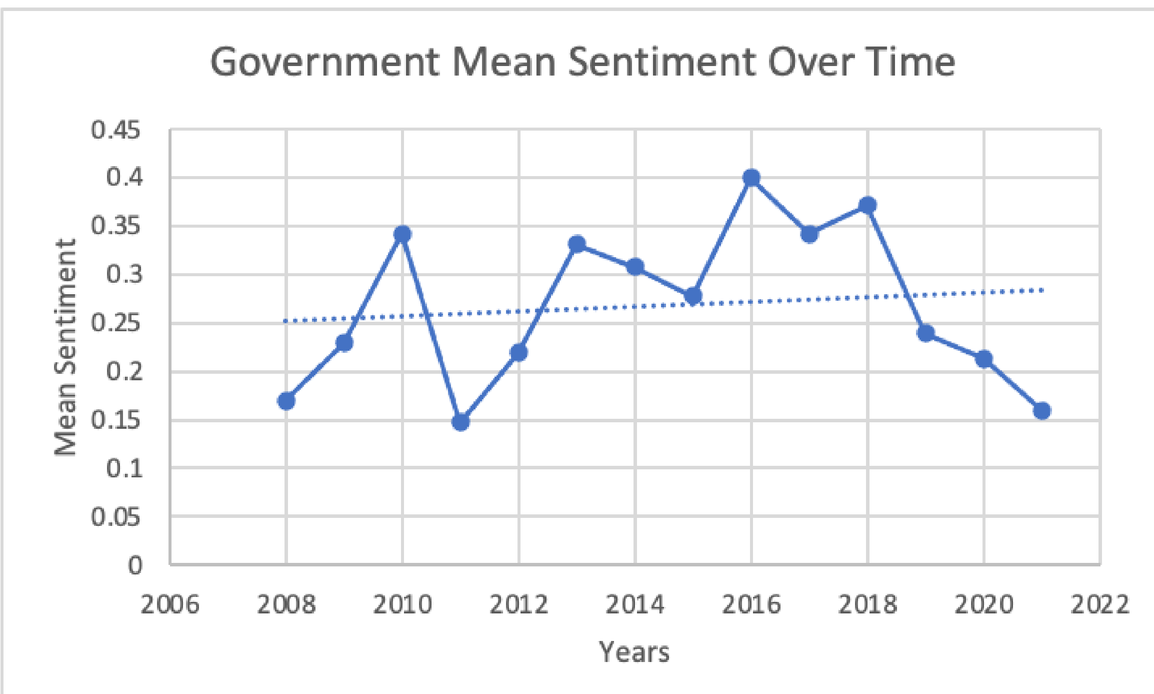

Figure H 4. Government mean sentiment over time

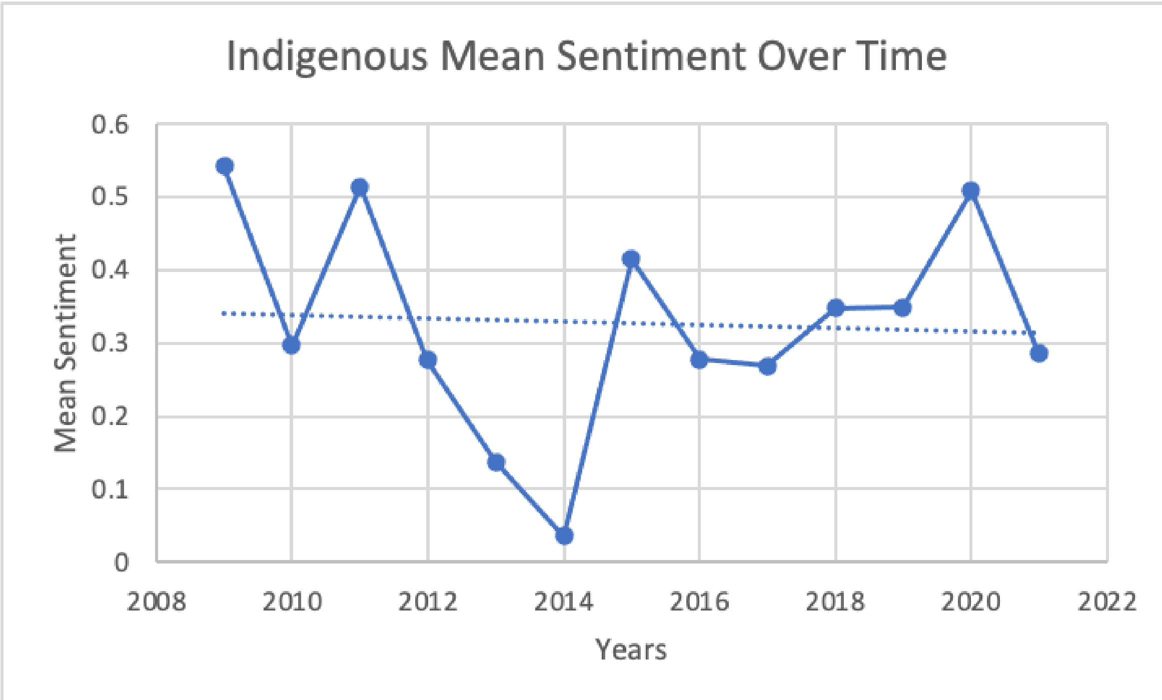

Figure H 5. Indigenous mean sentiment over time

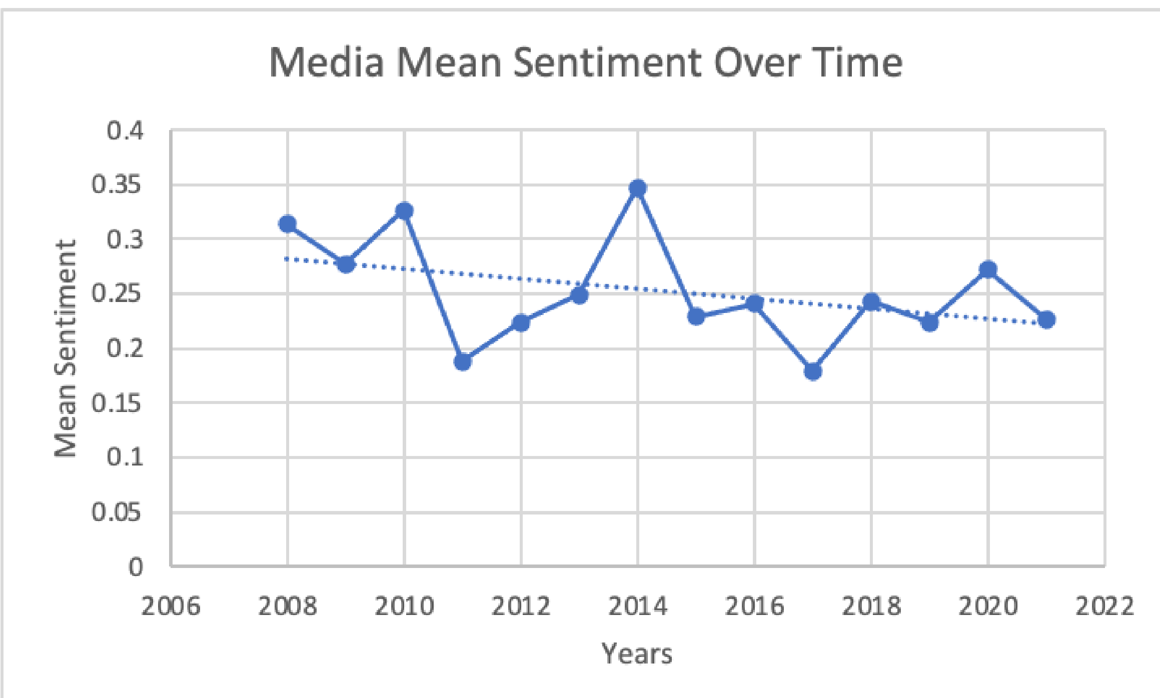

Figure H 6. Media mean sentiment over time

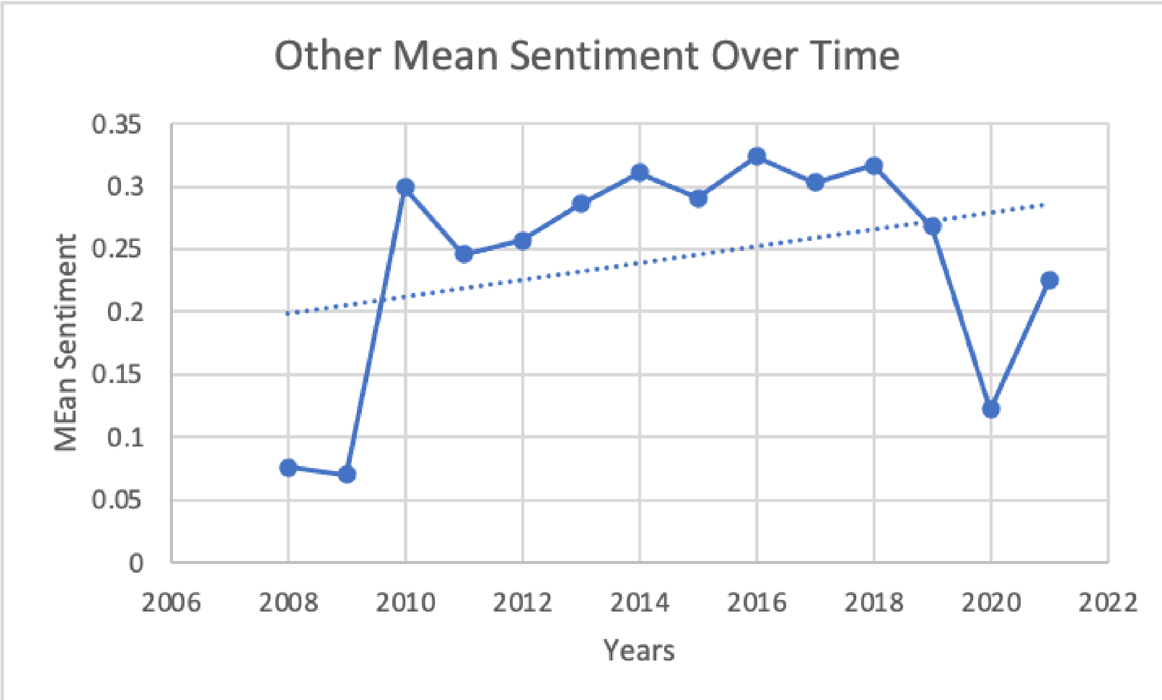

Figure H 7. Other mean sentiment over time

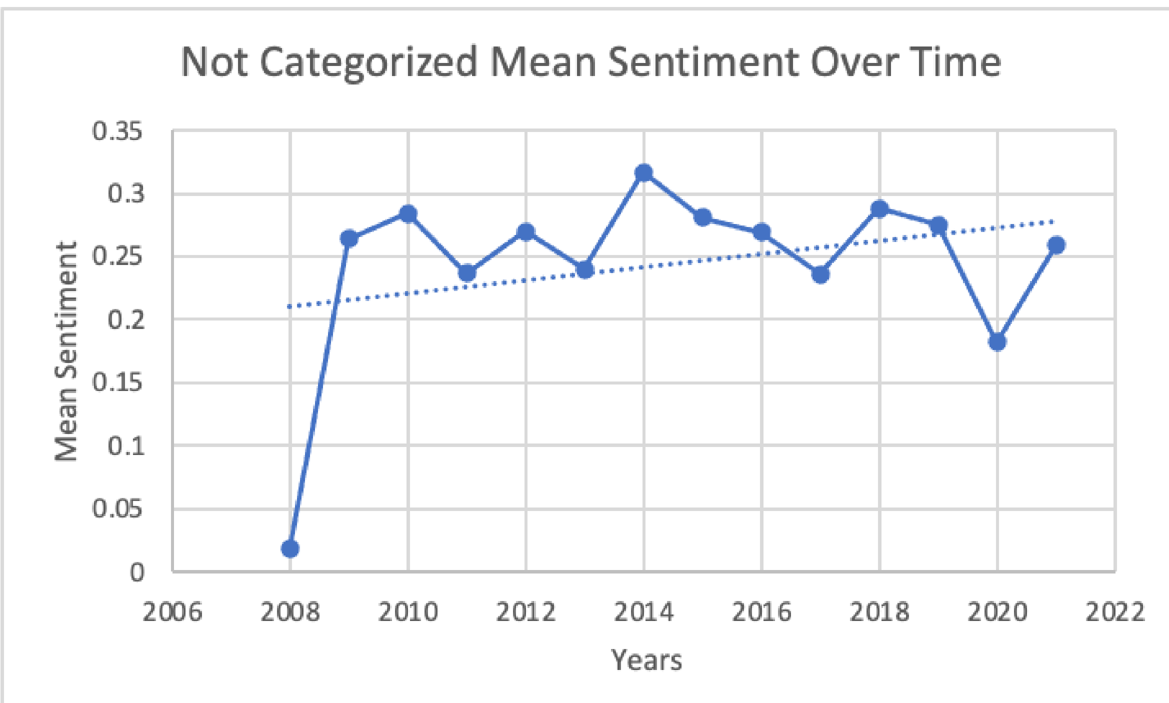

Figure H 8. No Category mean sentiment over time

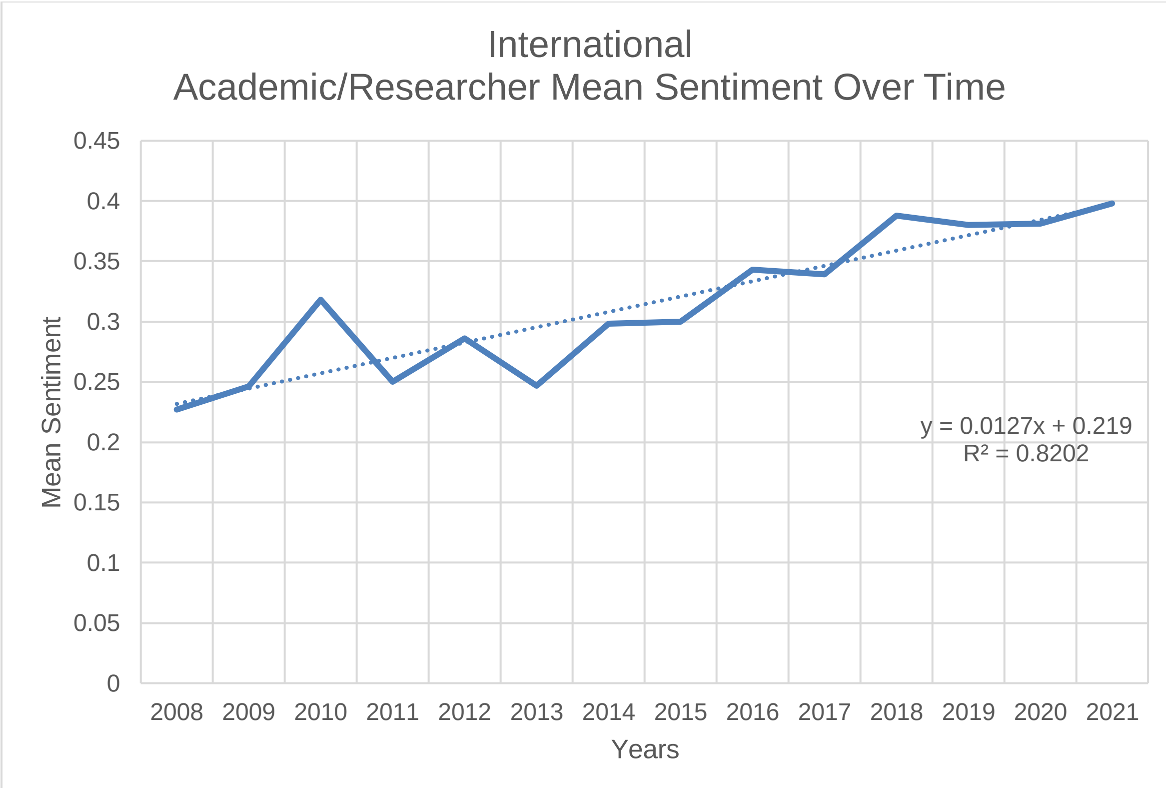

Figure H 9. International Academic/Researcher mean sentiment over time

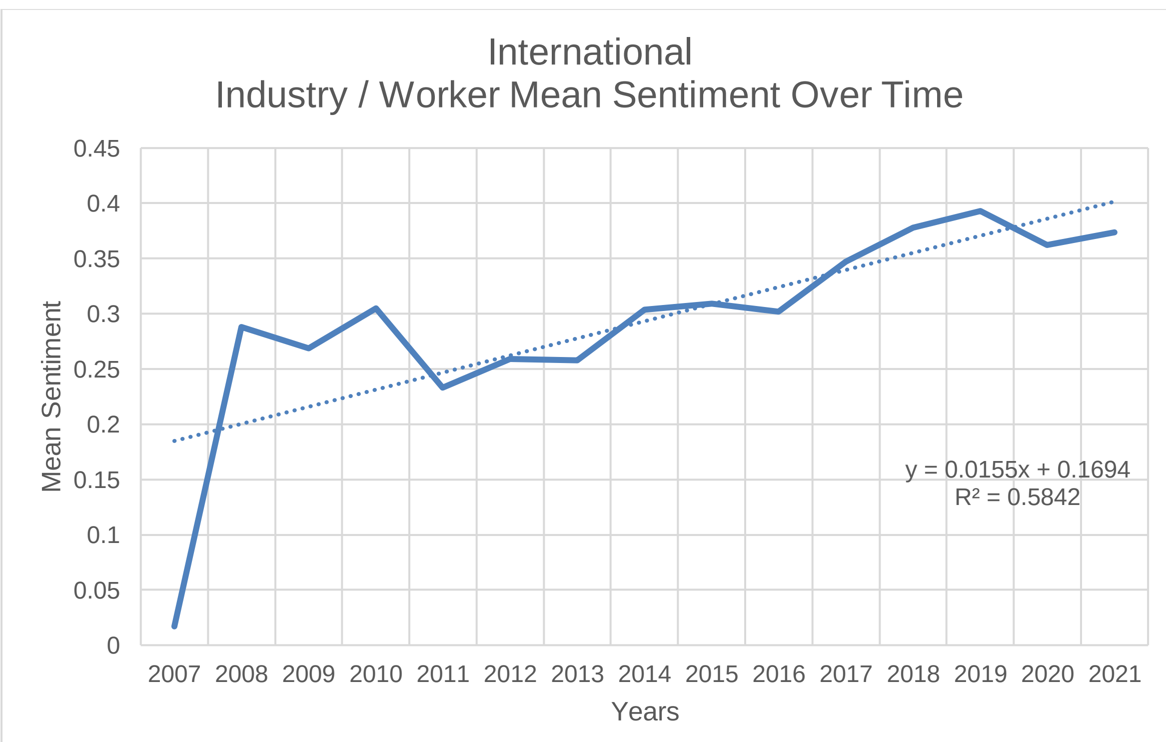

Figure H 10. International Industry/Worker mean sentiment over time

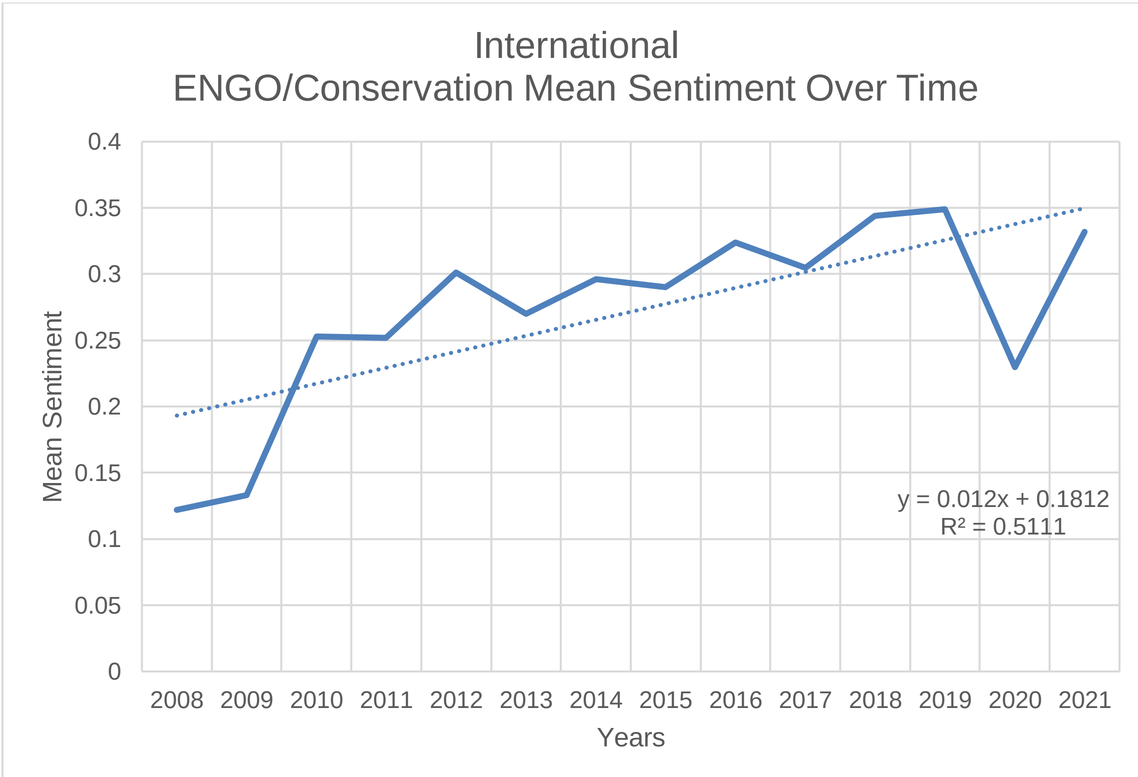

Figure H 11. International ENGO/Conservation mean sentiment over time

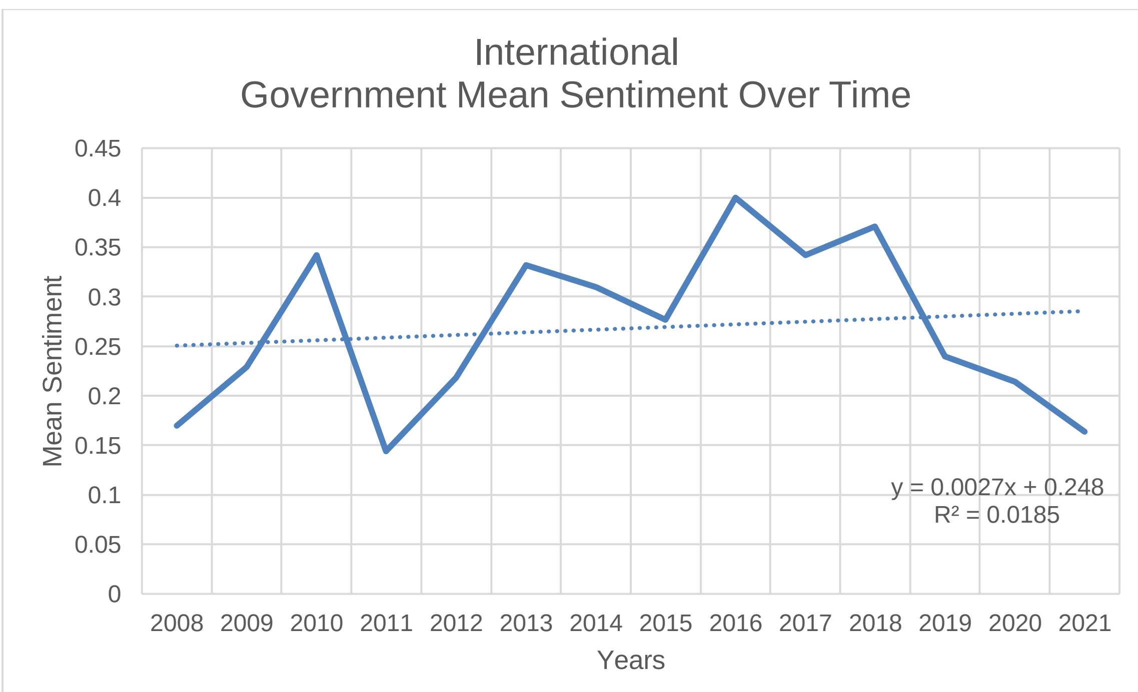

Figure H 12. International Government mean sentiment over time

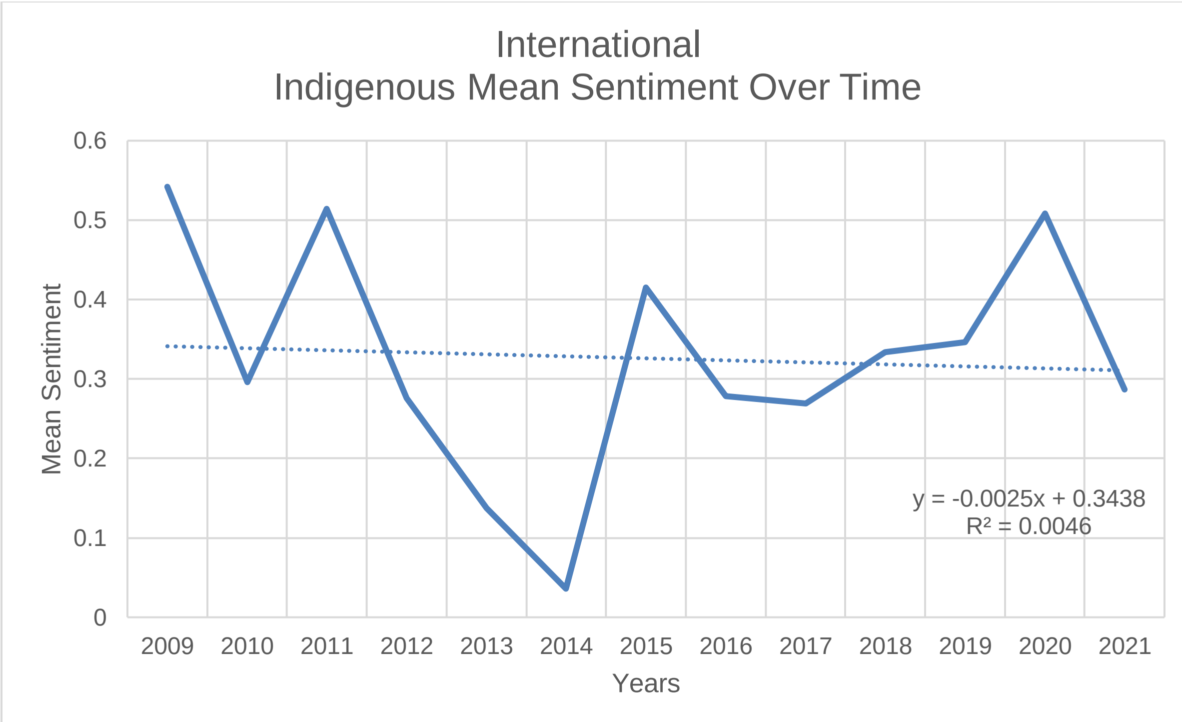

Figure H 13. International Indigenous mean sentiment over time

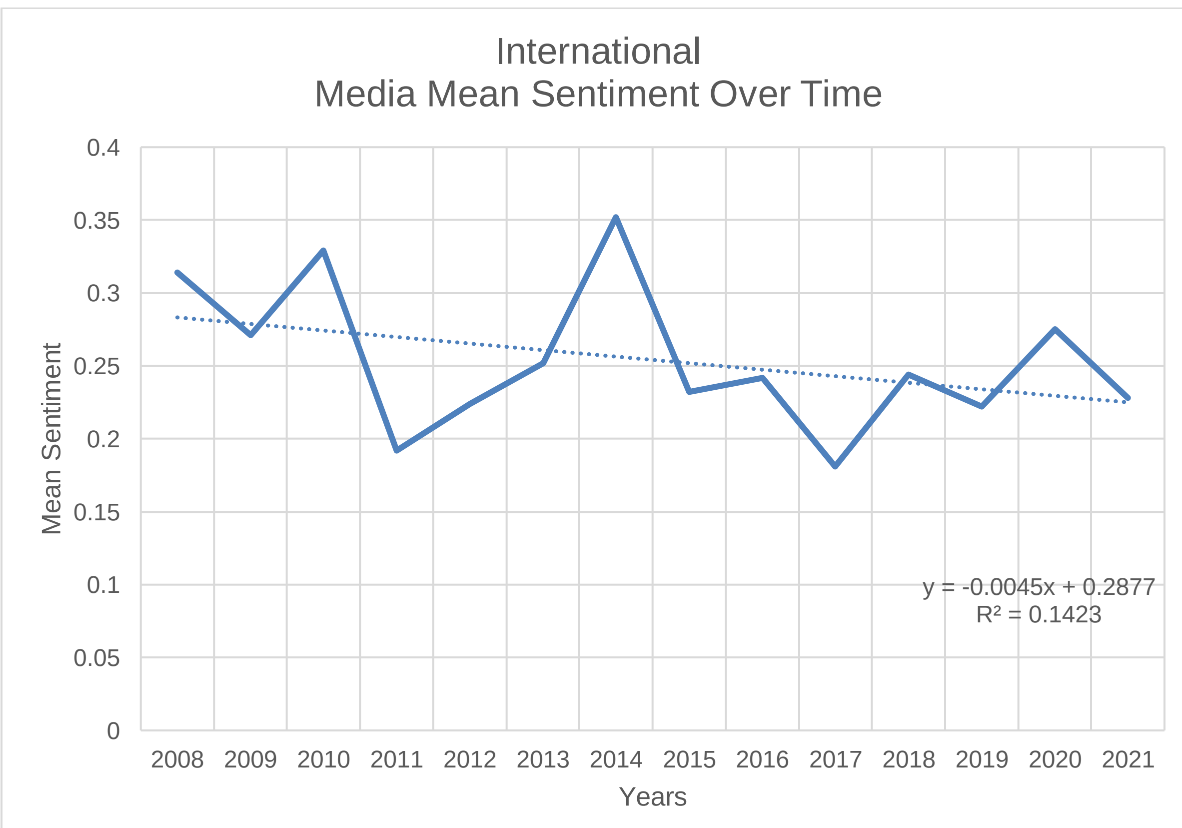

Figure H 14. International Media mean sentiment over time

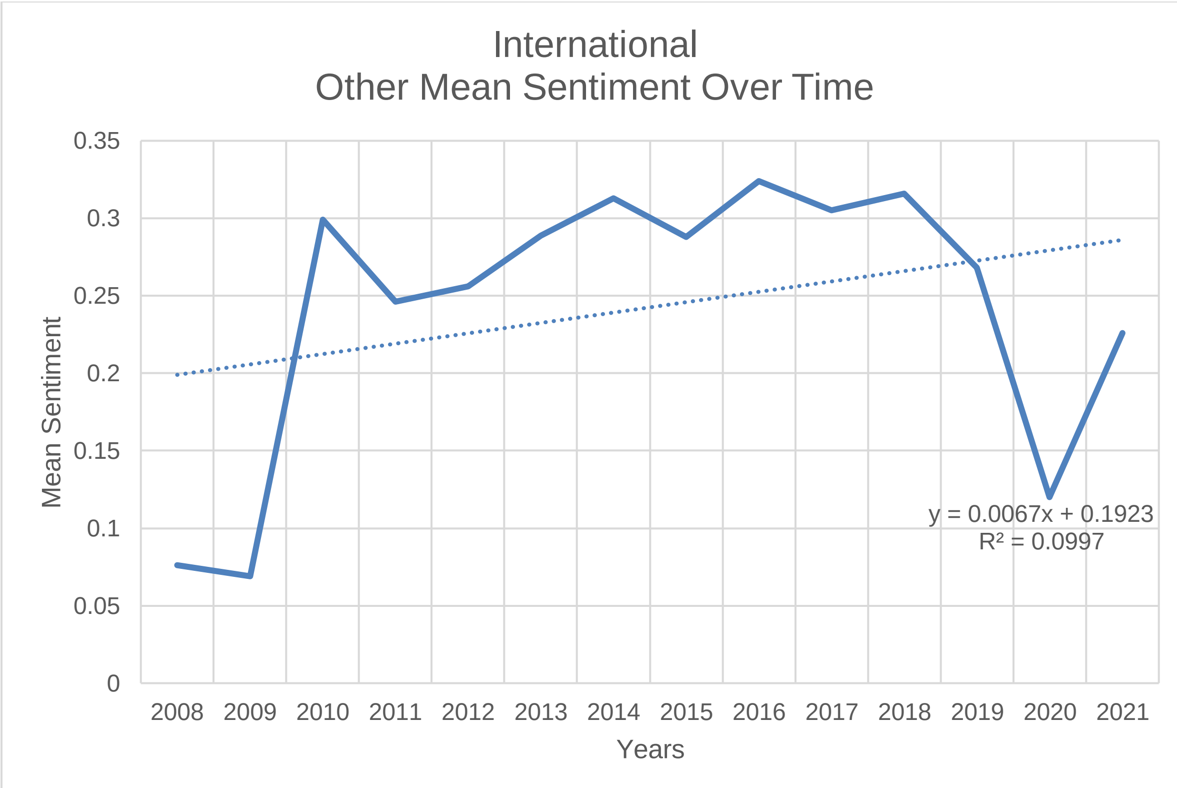

Figure H 15. International Other mean sentiment over time

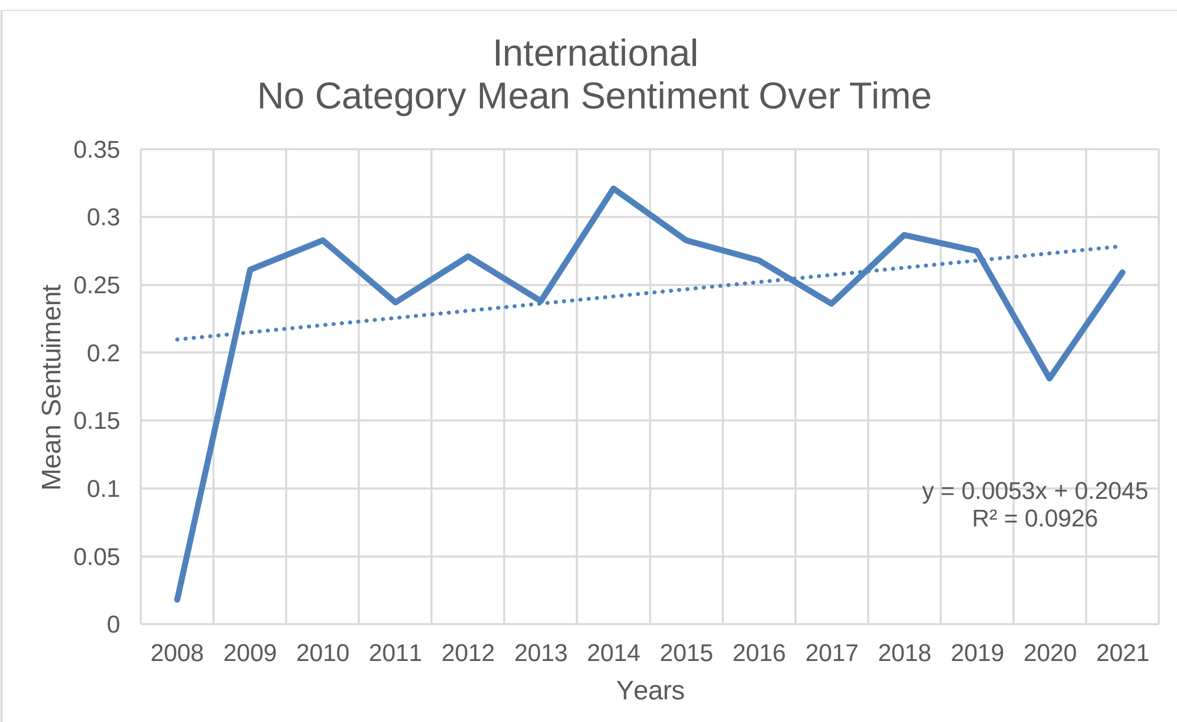

Figure H 16. International No Category mean sentiment over time

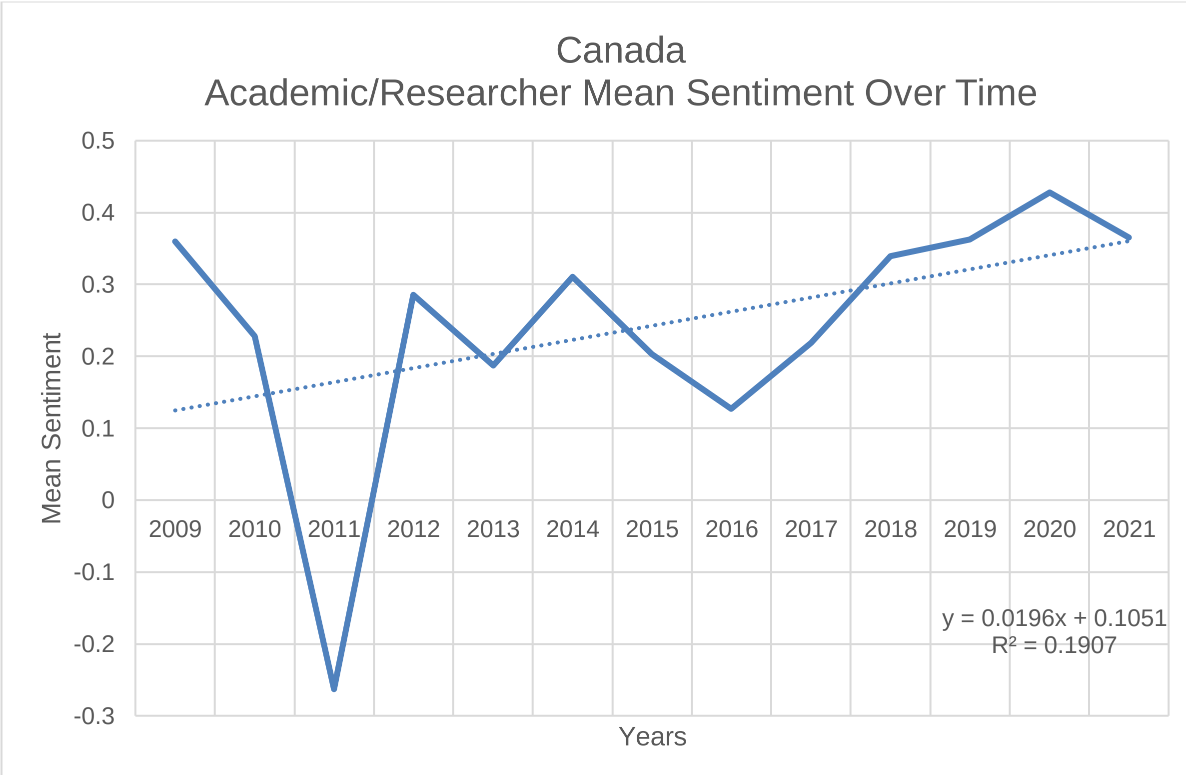

Figure H 17. Canada Academic/Researcher mean sentiment over time

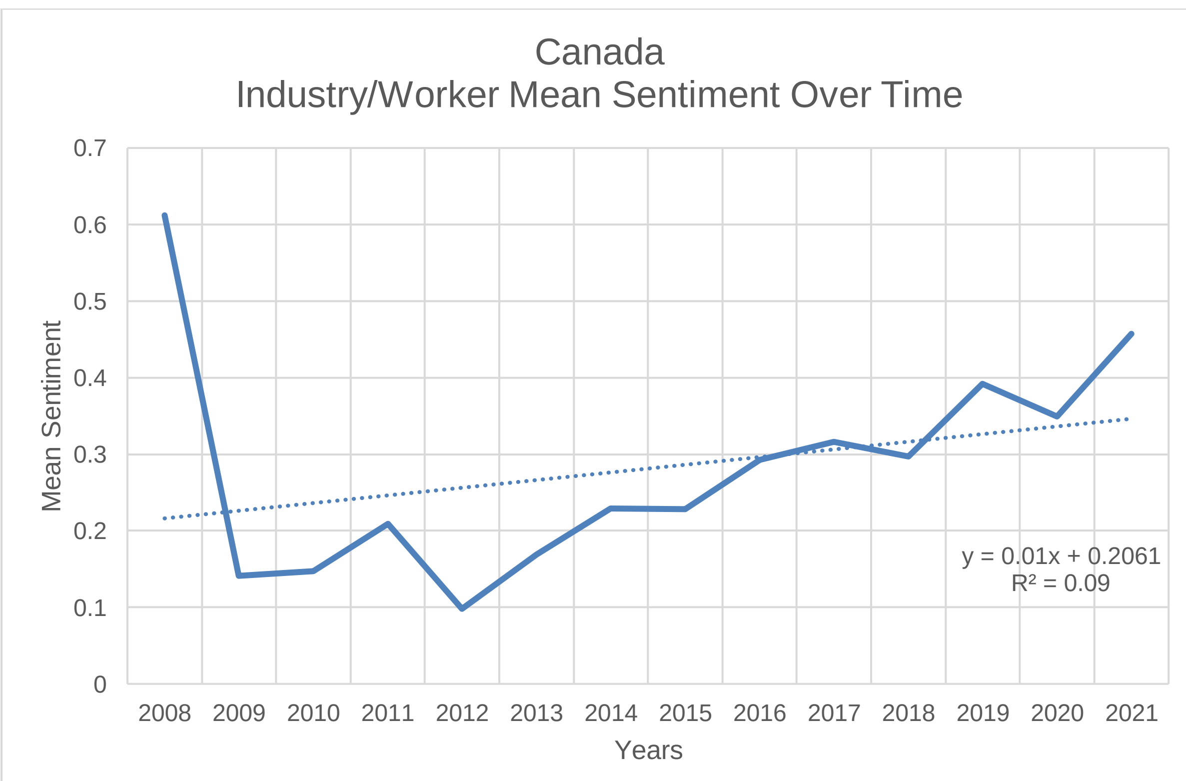

Figure H 18. Canada Industry/Worker mean sentiment over time

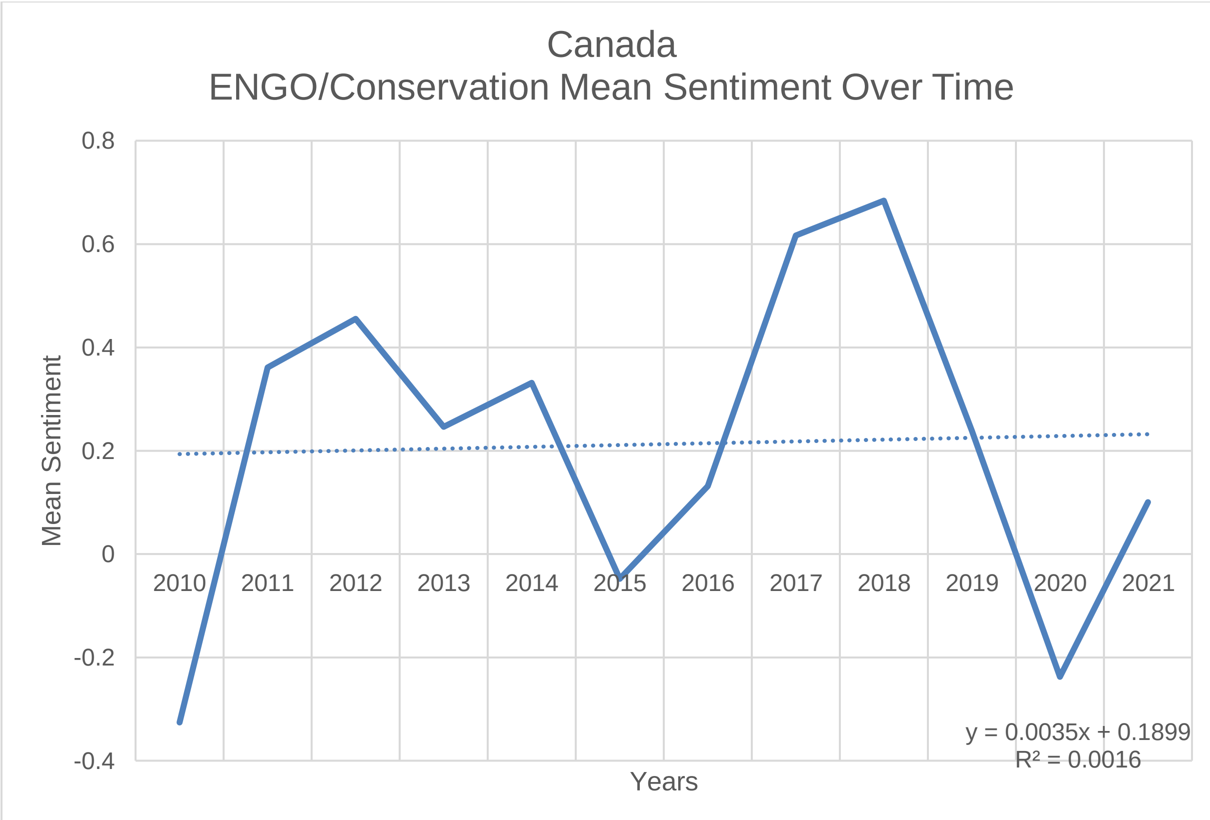

Figure H 19. Canada ENGO/Conservation mean sentiment over time

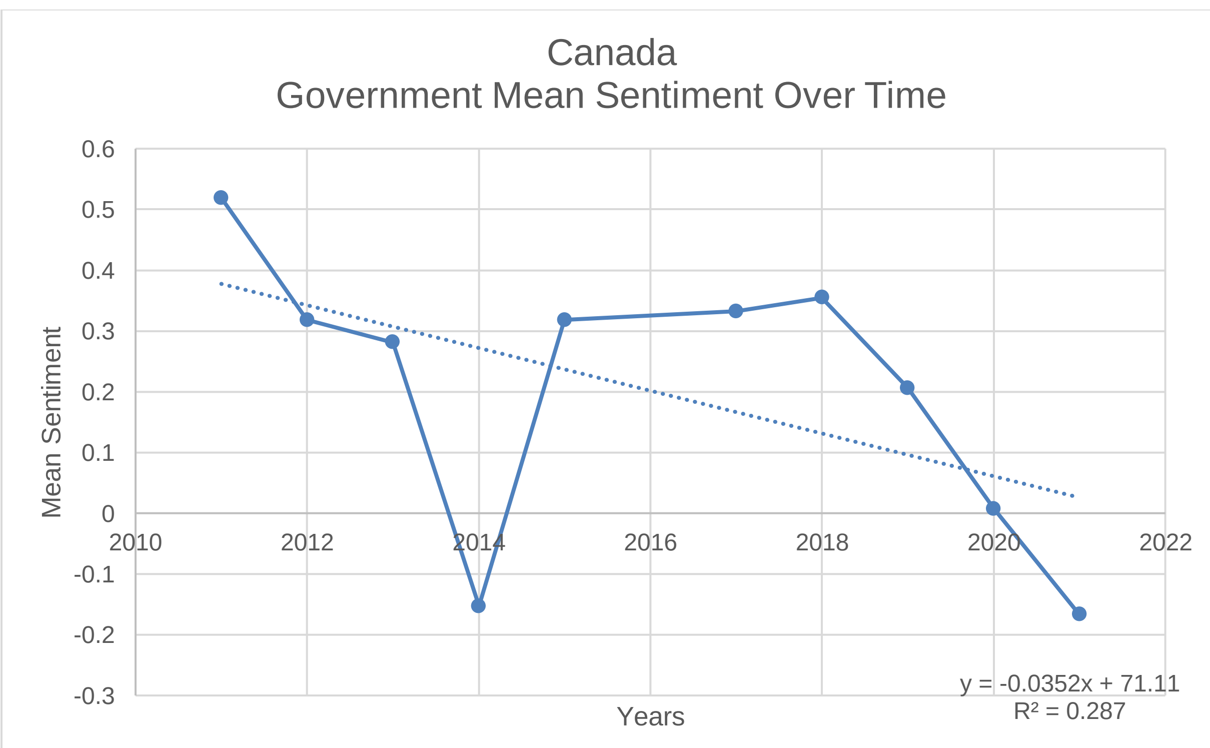

Figure H 20. Canada Government mean sentiment over time

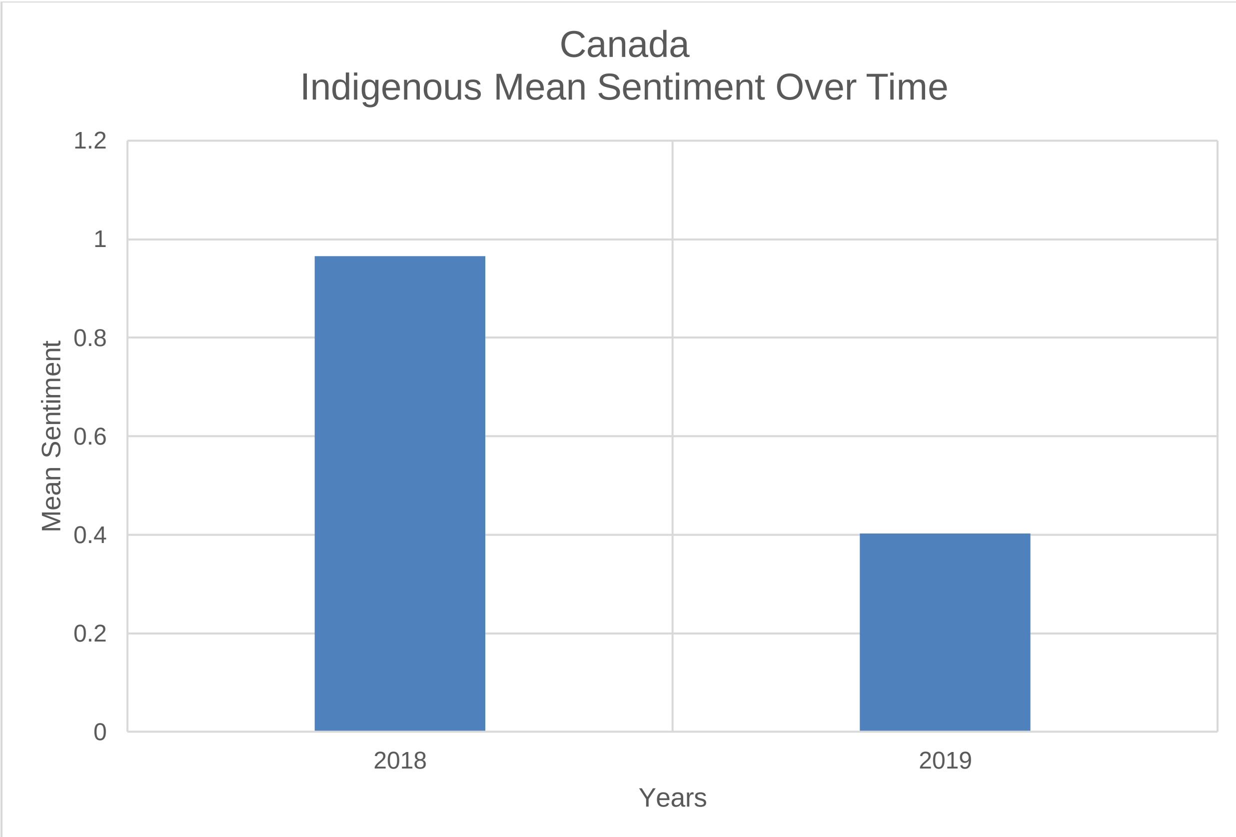

Figure H 21. Canada Indigenous mean sentiment over time

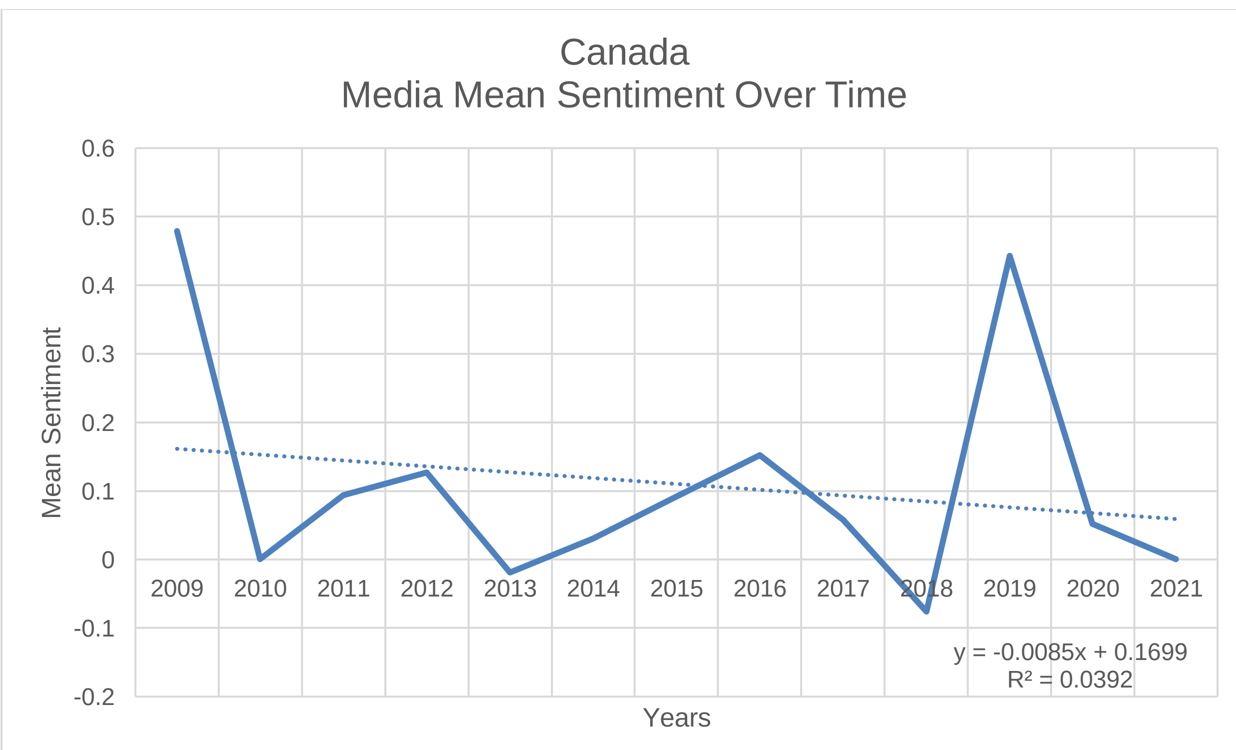

Figure H 22. Canada Media mean sentiment over time

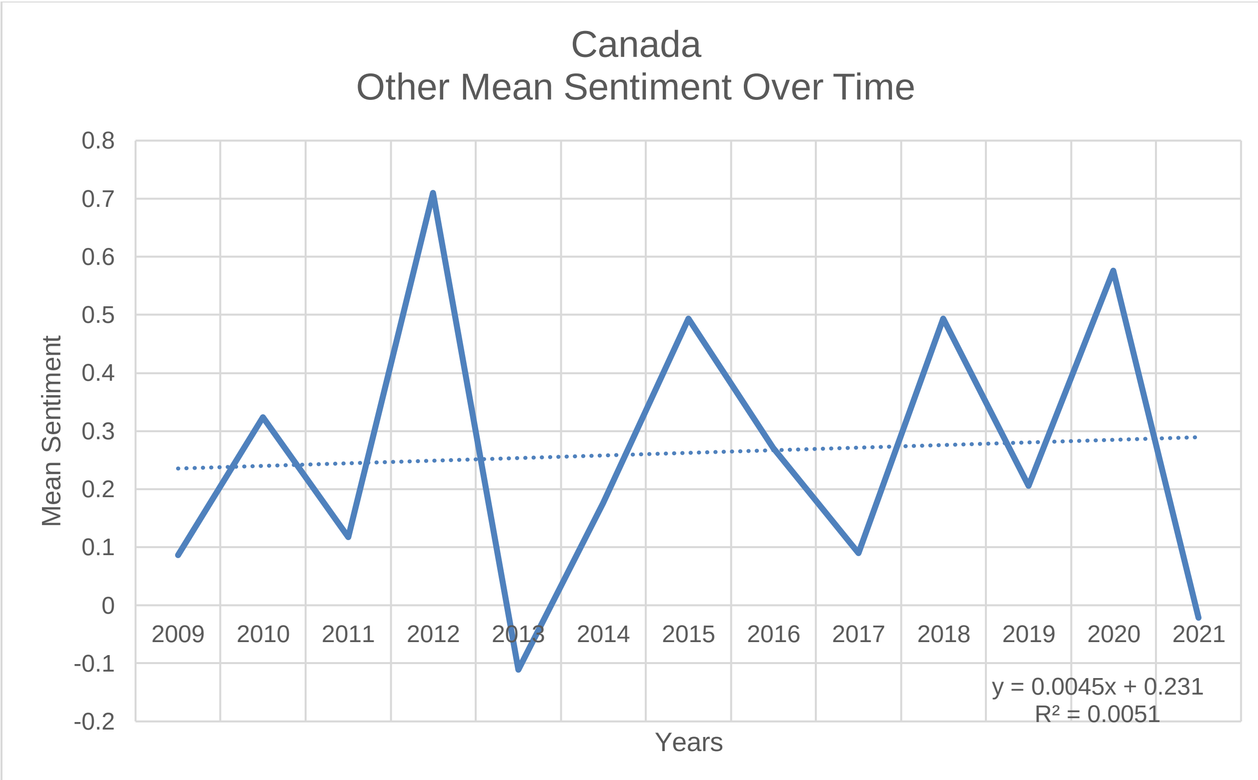

Figure H 23. Canada Other mean sentiment over time

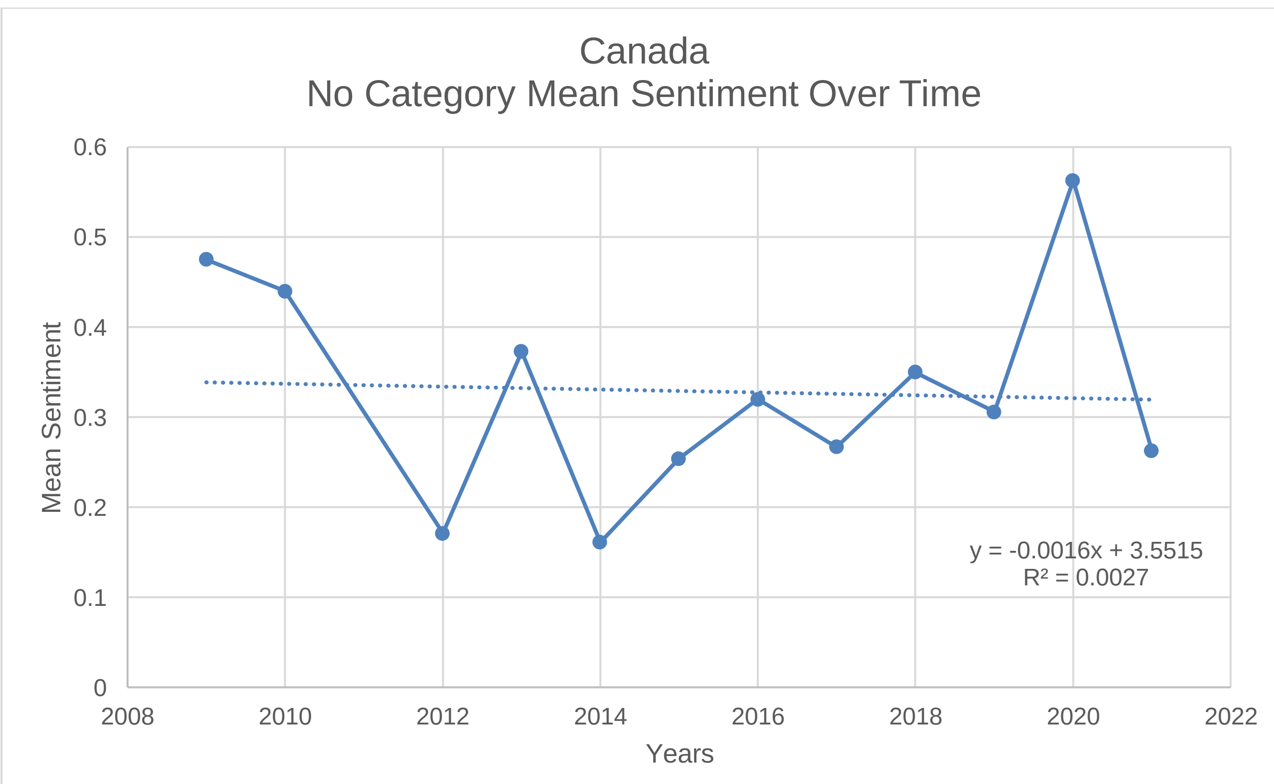

Figure H 24. Canada No Category mean sentiment over time