Torrential Twitter? Investigating the Severity of Harassment when Canadian Female Politicians Tweet about Climate Change*

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Women in politics face considerable online and offline harassment for their participation, especially when adopting strong policy stances on issues such as climate change. Known as gendertrolling, this specific form of harassment is often due to male climate deniers feeling threatened by the perceived power and qualifications of female politicians. This paper analyses Tweets which specifically discuss climate change from former MP Catherine McKenna, MP Elizabeth May, and MP Laurel Collins to investigate the severity of harassment on a seven-point scale and type of accounts behind the Tweets. This trial study reveals that nearly 80% of all Tweets contained some level of harassment, most frequently either questioning the authority of the MPs or calling them names/gender-based insults and came from accounts that were either suspended/deleted or personal users.

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*Code and other information available at: https://github.com/InessaDeAngelis/Torrential_Twitter_Trial

1 Introduction

Women in politics face considerable online and offline harassment, such as former Minister of the Environment and Climate Change Catherine McKenna and current Deputy Prime Minister Hon. Chrystia Freeland (Southern and Harmer 2021). Known as "gendertrolling," this harassment is part of a global trend of violence against women (Mantilla 2013; Wagner 2020). Gender-based harassment on Twitter is well documented in academic literature and inexplicably pro-environmental behaviors are often viewed as "feminine" (Citron 2014; Vickery and Everbach 2018; Anshelm and Hultman 2014). Female politicians who adopt strong policy stances are more likely to face online misogyny and harassment because it is not consistent with existing gender stereotypes and notions of power, and poses a threat to male climate deniers (Courtemanche and Connor Green 2020; Rheault, Rayment, and Musulan 2019; Geus et al. 2021)

To gain a deeper understanding of the intersection of climate change denialism and online gendered-harassment faced by Canadian female politicians, I measure the severity of harassment former Liberal Party MP Catherine McKenna, Green Party MP Elizabeth May, and New Democratic Party MP Laurel Collins receive when Tweeting about climate change on a seven-point scale, using Tweets sent leading up to and during the 2019 Federal election. I then analyse the types of accounts behind the Tweets sent to MP McKenna, MP May, and MP Collins.

Harassment or gendertrolling is defined as sexist or misogynistic remarks that target a person based on their gender or sexuality and have varying levels of severity (Wagner 2020). Severity of harassment includes:

1. Positive
2. Neutral
3. Questioning Authority
4. Name-calling/Gender insults
5. Vicious language
6. Credible threats
7. Hate speech

Type of account is defined as the dynamics of relationships between followers, followings, and lists and will be determined by analyzing the accounts' bio, profile image, and other characteristics (Singh, Bansal, and Sofat 2018; Uddin, Imran, and Sajjad 2014) and includes:

1. Personal
2. Professional

3. Bots
4. Spammers
5. Anonymous
6. Suspended/Deleted

My analysis emphasizes that nearly 80% of the Tweets in my sample contained some level harassment, ranging from questioning authority to hate speech, while the remaining Tweets had either positive or neutral sentiments. Questioning the authority of female politicians or name-calling/offering up gender-based insults were the most common forms of harassment identified, accounting for 75% of all Tweets and harassing Tweets were most likely to be sent from Suspended/deleted or personal Twitter accounts. Statistically speaking, there was little difference between the severity of harassment faced by MP McKenna and MP May, although there were distinguishable qualitative differences. My Discussion section further explores these key findings and others of note.

In the remainder of this paper, I commence with the Data section which outlines the nature of the data used for this trial study, limitations, coding, and cleaning procedures. In the Results section, I present trends found during the analysis process, followed by more insights in the Model section. Then, in the Discussion section, I provide further insights and outline areas where my thesis will differ from this trial study. Finally, in the Conclusion, I summarize the main findings.

1.1 Theoretical Framework

This study will be conducted under the theory of deliberative democracy which emphasizes having open, respectful, and diverse discourse for a healthy democracy (Pain and Masullo Chen 2019; Trifiro et al. 2021). Democratic legitimacy is established by allowing the public to collectively participate in deliberation about consequential decisions, while recognizing there are multiple viewpoints on every issue, including climate change (McKay and Tenove 2021; Chen 2017).

Results from the analysed Tweets will be compared to the aforementioned definition to see if the level of discourse about climate change on Twitter matches the characteristics of what is considered healthy discourse under the theory of deliberative democracy.

2 Data

The data used in this paper was collected via Twitter's API in early 2021 for a separate research project I undertook during my undergraduate degree and has since been stored on my personal Mac. A more detailed discussion of the dataset composition and the collection process can be found in Appendix A.

2.1 Data Limitations

Twitter, the platform's affordances, and the types of accounts and content circulate is ever-changing. Consequently, Tweets authored in 2019, collected in 2021, and analysed for this trial study in 2023 are faced with changing contexts and affordances which must be accounted for. There are potential inaccuracies in reporting which accounts are still on the platform and which have been suspended/deleted, especially following successive waves of Covid-19 mis- and dis-information on the platform. Although this was anticipated, some users do not have bios or locations indicated (listed as NA), which may impact how `type of account` is coded. The sheer volume of Tweets collected in 2021 also means that only a small sample is being used for this trial study, impacting the ability to broadly generalize results.

During the 2019 Federal election campaign, MP Collins was a City Councillor in Victoria, BC, never having been elected to the House of Commons or faced the scrutiny of traditional and social media on a national level. This means that she received far fewer Tweets during the same period as MP McKenna and MP May and that the results from her portion of the study are less generalizable, but are still important to include given her increased profile in 2023 and anticipated prominence in the full-scale version of this study.

A major limitation of using Twitter data for any research project, including this one, is the inability to determine a representative sample of voting-age Canadians and draw generalizable results about public opinion on any given issue (Bermingham and Smeaton 2011). Selection bias exists because Twitter tends to only represent the views of people who are "… more partisan, polarized, and uncivil" and motivated to be active users (McGregor 2020, 237). We are also limited by the information users choose to publicly display on their profiles, such as their location, so it is not always possible to confirm if an individual is Canadian or other identifying demographic information (Holmberg and Hellsten 2015).

Moreover, Twitter data is collected as a snapshot in time, often reducing users to a single interaction on the platform, meaning we cannot see their full range of political expressions and frequency of certain behaviours, leading to potential measurement bias. Consequently, with context collapse which happens when an individual user's Tweets are taken out of the context and imagined audience in which they were intended for, users' true political beliefs, views on climate change, and perspectives on the qualifications of women in politics may be misrepresented (Marwick and Boyd 2011). Some users may also show up more than once in the dataset if they are prolific Twitter users, leading to overrepresentation of their views and type of account. With these identified limitations in mind, results should be considered in the context of this study and generalizations can only be reflective of the users in the dataset and not the wider Canadian public.

2.2 Data Coding

This trial study employs a novel approach of conducting quantitative content analysis, combining the level of nuance and detail captured in qualitative content analysis and interviews (Wagner 2020; Erikson, Håkansson, and Josefsson 2021) with more binary quantitative methods (Theocharis et al. 2020; Rheault, Rayment, and Musulan 2019). By offering this quantitative, seven-point scale to measure the severity of harassment, we can begin to better understand the full extent of harassment faced by Canadian female politicians and work toward implementing solutions.

To code the Tweets, I developed a Codebook to standardize the coding process and designed a Google Form (available in Appendix B) which allows coders to enter key information about each Tweet to determine the severity of harassment and type of account. Coders code `severity of harassment` on the previously discussed seven-point scale based on the Tweet text provided in the dataset. `Type of account` was determined by coders by looking at a user's username, display name, and bio displayed in the static dataset and then by logging into Twitter to look at the "dynamics" including the user's profile and header pictures and frequency of replies and likes, as it stands of July 2023 on Twitter (Singh, Bansal, and Sofat 2018). Although a significant amount of time has passed between when the Tweet was originally authored, collected, and coded for this project, it was determined that this was the best approach for this trial study, but will be re-evaluated for the full-scale study.

2.3 Data Cleaning

Data was collected via Twitter API using Python (see datasheet in Appendix A for more information) and cleaned, tested, modeled, and analysed using the statistical programming software R (R Core Team 2023), using functions from `tidyverse` (Hadley Wickham et al. 2019), `ggplot2` (Hadley Wickham 2016), `tayloRswift` (Stephenson 2021), `janitor` (Firke 2023), `KableExtra` (Zhu 2021), `knitr` (Xie 2014), `here` (Müller and Bryan 2020), `formattable` (Ren and Russell 2021), `arrow` (Richardson et al. 2023), `validate` (Van der Loo, De Jonge, and Hsieh 2023), `testthat` (H. Wickham 2023), `rstanarm` (Goodrich et al. 2023), `gtsummary` (Daniel et al. 2021), `marginaleffects` (Arel-Bundock 2023), and `modelsummary` (Arel-Bundock 2022).

The data utilized in this trial study underwent two rounds of cleaning: the first was to clean and select the Tweets to manually code and the second was to clean the coded Tweets to prepare for analysis and visualization.

2.3.1 Raw Data

In preparation to code my Tweets for `severity of harassment` and `type of account`, I first had to eliminate extra information in the datasets and take a sample, given that there were

116,649 Tweets between the three politicians in the raw datasets.

After retrieving the datasets from my archived files, I performed the first round of data cleaning based on the design of my trial study. I removed the columns which presented information not required for this study, including a previously assigned toxicity score determined by Perspective API (see Appendix A). Then, using the `filter` function, I filtered all Tweets by the key word "climate", and then took a sample using the `slice_sample` function of 500 Tweets from both MP McKenna and MP May's datasets. Only 13 Tweets from MP Collins matched the criteria, so there was no need to take a sample.

I renamed columns and capitalized the first letter of every word using Twitter Developer's guidelines and my Codebook (Developer 2023). I renamed `text` to `Text`, `user_name` to `Name`, `user_sname` to `Username`, `user_description` to `Bio`, `user_location` to `Location`, `followers` to `Followers`, `friends` to `Following`, and `tweet_URL` to `URL`.

I then tested the raw data using the `testthat` (H. Wickham 2023) package to ensure the dataset was ready to be manually coded.

2.3.2 Coded Data

After coding the 1,013 Tweets manually using my Google form (see Appendix B), I then visually checked for missing data, such as Tweet URLs, name of politicians, and severity of harassment that I forgot to add the first time, and went back and re-coded the few Tweets that contained missing information. I also conducted random spot checks to ensure that all Tweets were consistently coded based on the definitions and examples in my Codebook, since there is only one coder for this study. A number of Twitter accounts opted not have bios (listed as NA in the datasets), which is missing data that was anticipated within the datasets. After my dataset passed this initial test, I proceeded to clean it a second time using R.

For my `severity of harassment` data, I updated value 1 to "Positive", 2 to "Neutral", 3 to "Questioning authority", 4 to "Name-calling/Gender insults", 5 to "Vicious language", 6 to "Credible threats", and 7 to "Hate speech" based on my Codebook.

For my `type of account` data, I changed value 1 to "Personal", 2 to "Professional", 3 to "Bots", 4 to "Spammers", 5 to "Anonymous", and 6 to "Suspended/deleted" based on my Codebook.

I tested the cleaned data using the `validate` (Van der Loo, De Jonge, and Hsieh 2023) package, primarily validating variable types and ensuring all Tweets were coded (500 for both MP McKenna and MP May and 13 for MP Collins).

Table 1: Breakdown of Severity of Harassment on the seven-point scale detected in Tweets to all three politicians

Severity of Harassment	Number of Responses	Percent
Positive	24	2.4%
Neutral	208	20.5%
Questioning Authority	522	51.5%
Name-calling/Gender insults	243	24.0%
Vicious language	12	1.2%
Credible threats	2	0.2%
Hate speech	2	0.2%

3 Results

3.1 Severity of Harassment

Among the 1,013 Tweets selected for content analysis from the three MPs, 522 (51.5%) Tweets were identified as **Questioning authority**, 243 (24.0%) as **Name-calling/Gender insults**, and 208 (20.5%) as **Neutral**. 24 (2.4%) Tweets were coded as **Positive**, 12 (1.2%) as **Vicious language**, while 2 Tweets (or 0.2%) were identified for both the **Credible threats** and **Hate speech** categories (see Table 1).

Figure 1 illustrates that the `severity of harassment` detected across the Tweets mentioning all three female politicians have some commonalities, but also differences depending on the politician. Just over half of both MP McKenna and MP May's Tweets were categorized as **Questioning Authority**, while MP Collins only had 2 Tweets that questioned her authority. The next most frequent level of harassment detected for MP McKenna was **Name-calling/Gender insults** which accounted for 30% of all Tweets, while MP May's next most frequent type of harassment was **Neutral** at almost 30%. In contrast, the third most frequent level of harassment detected for MP McKenna was **Neutral**, with 10% of Tweets, while MP May's next most frequent level of harassment was **Name-calling/Gender insults**, accounting for almost 20% of Tweets. MP Collins' remaining 85% of Tweets were categorized as **Neutral**.

For both MP McKenna and MP May, the remaining levels of harassment including **Positive**, **Vicious language**, **Credible threats**, and **Hate Speech** differed to some degree, as emphasized by Figure 1. 2% of MP McKenna's Tweets were **Positive** while 3% of the Tweets sent to MP May had a **Positive** tone. 2% of MP McKenna's Tweets contained **Vicious language** while less than 1% of the Tweets sent to MP May contained **Vicious language**. **Credible threats** and **Hate Speech** accounted for less than 1% of the Tweets sent to MP McKenna, with MP May having no **Credible threats** detected among the Tweets sent to her and less than 1% containing **Hate Speech**.

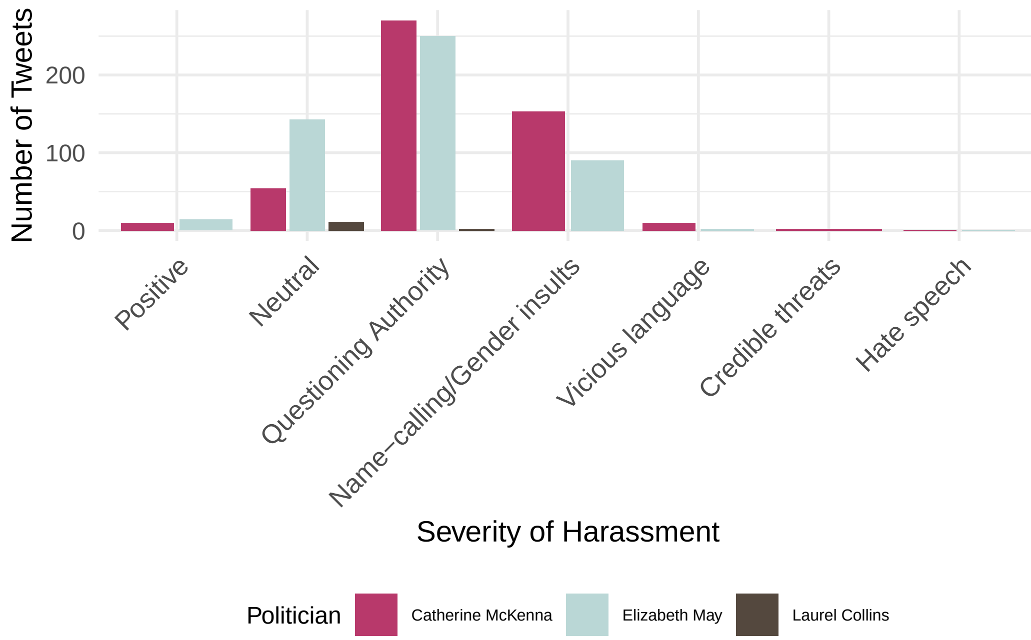

Figure 1: Breakdown of Severity of Harassment on the seven-point scale detected in Tweets and organized by politician

3.2 Type of Account

Of the accounts behind the Tweets sent to the three politicians, 422 (41.7%) were identified as **Suspended/deleted**, 327 (32.3%) as **Personal**, and 150 (14.8%) as **Anonymous**. 102 (10.1%) were coded as **Professional**, 11 (1.1%) as **Spammers**, while 1 account (or 0.1%) was identified as a **Bot** (see Table 2).

Figure 2 illustrates that the `types of accounts` detected as being behind the Tweets sent to the three female politicians share some common features, but also differences depending on the politician. Just over 40% of Tweets sent to MP McKenna came from **Suspended/deleted** users while just under 40% of Tweets sent to MP May came from **Suspended/deleted** users. Approximately 25% of Tweets sent to MP McKenna came from a **Personal** account while nearly 40% of Tweets sent to MP May came from a **Personal** account. **Anonymous** accounts were the third most frequent type of account detected for MP McKenna, sending just over 20% of the Tweets in her sample. Conversely, the third most frequent type of account detected for MP May was **Professional**, responsible for sending just under 15% of the Tweets in her sample. The `types of accounts` responsible for sending Tweets to MP Collins were **Professional** users (70%), followed by **Personal** users (almost 25%), and then **Suspended/deleted** users (just under 5%).

For the fourth most common `type of accounts` identified, just over 5% of Tweets sent to

Table 2: Breakdown of Types of Accounts detected in Tweets sent to all three politicians

Type of Account	Number of Responses	Percent
Personal	327	32.3%
Professional	102	10.1%
Bots	1	0.1%
Spammers	11	1.1%
Anonymous	150	14.8%
Suspended/deleted	422	41.7%

MP McKenna came from **Professional** accounts while MP May received just under 10% of Tweets from **Anonymous** accounts (see Figure 2). The remaining 2% of Tweets received by MP McKenna came from **Spammers**, while **Spammers** and **Bots** combined were responsible for sending less than 1% of the remaining Tweets to MP May. Both MP McKenna and Collins had no **Bots** detected.

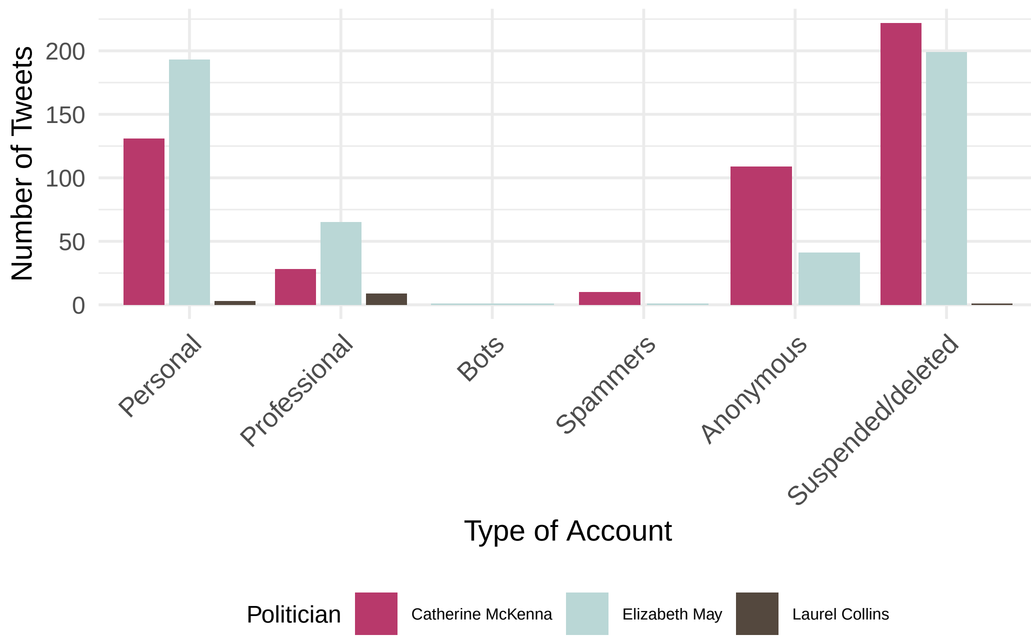

Figure 2: Type of Accounts behind the Tweets received, broken down by politician

Table 3: Breakdown of the Severity of Harassment on the seven-point scale detected among MP McKenna's Tweets

Severity of Harassment	Number of Responses	Percentage
Positive	10	2.0%
Neutral	54	10.8%
Questioning Authority	270	54.0%
Name-calling/Gender insults	153	30.6%
Vicious language	10	2.0%
Credible threats	2	0.4%
Hate speech	1	0.2%

Table 4: Breakdown of the Types of Accounts detected among MP McKenna's Tweets

Type of Account	Number of Responses	Percentage
Personal	131	26.2%
Professional	28	5.6%
Spammers	10	2.0%
Anonymous	109	21.8%
Suspended/deleted	222	44.4%

3.3 Catherine McKenna

Among the sample of 500 Tweets sent to MP McKenna, 270 (54%) were identified as **Questioning authority**, 153 (30.6%) as **Name-calling/Gender insults**, and 54 (10.8%) as **Neutral** for `severity of harassment`. 10 Tweets (2.0%) were identified for both the **Positive** and **Vicious language** categories, while 2 Tweets (0.4%) contained **Credible threats** and 1 Tweet (0.2%) contained **Hate speech** (see Table 3).

For `Type of account`, 222 (44.4%) were identified as **Suspended/deleted**, 131 (26.2%) as **Personal**, 109 (21.8%) as **Anonymous**, 28 (5.6%) as **Professional**, and 10 (2.0%) as **Spammers**, with no **bots** being detected (see Table 4).

Figure 3 emphasizes the relationship between the `severity of harassment` faced by MP McKenna and the `type of accounts` behind the Tweets. The few **Positive** Tweets received by MP McKenna were most likely to be sent by **Personal** users (1%), **Professional** users (0.6%), or **Suspended/deleted** users (0.4%), while **Neutral** Tweets came from accounts categorized as **Professional** (3.8%), **Suspended/deleted** (3.6%), and **Personal** (2.4%). **Anonymous** users and **Spammers** did not send **Positive** Tweets to MP McKenna. Tweets coded as **Questioning Authority** were most frequently sent by **Suspended/deleted** users (22.6%), followed by **Personal** users (15.6%), and **Anonymous** users (13.4%). The Tweets containing **Name-calling/Gender insults** were most frequently sent by users identified as **Suspended/deleted** (16.2%), **Anonymous** (7.0%), or **Personal** (6.8%). **Vicious language** identified Tweets were sent by **Suspended/deleted** users (1.2%), **Anonymous** users (0.4%), and **Spammers** (0.2%). The identified instances of **Credible threats** and **Hate speech** were sent by **Suspended/deleted** accounts and **Bots** did not send any Tweets to MP McKenna.

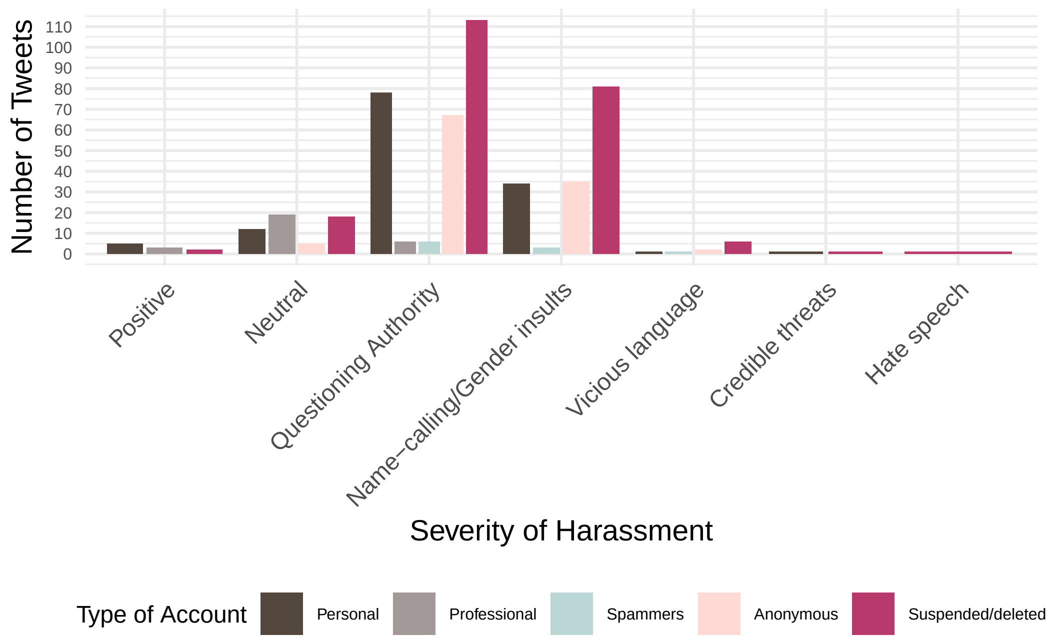

Figure 3: Relationship between Severity of Harassment and Types of Accounts detected among MP McKenna's Tweets

3.4 Elizabeth May

Among MP May's sample of 500 Tweets, 250 (50.0%) were identified as **Questioning authority**, 143 (28.6%) as **Neutral**, and 90 (18.0%) as **Name-calling/Gender insults** for `severity of harassment`. 14 Tweets (2.8%) were identified as being **Positive**, while 2 Tweets (0.4%) contained **Vicious language**, and 1 Tweet (0.2%) contained **Hate speech** (see Table 5). No Tweets containing **Credible threats** were detected in this sample.

For `Type of account`, 199 (39.8%) were detected as **Suspended/deleted**, 193 (38.6%) identified as **Personal**, 65 (13.0%) as **Professional**, and 41 (8.2%) as **Anonymous**. 1 (0.2%) of both **Bots** and **Spammers** were detected (see Table 6).

The relationship between the `severity of harassment` faced by MP May and the `type of accounts` behind the Tweets can be observed in Figure 4. **Positive** Tweets were sent by

Table 5: Breakdown of the Severity of Harassment on the seven-point scale detected among MP May's Tweets

Severity of Harassment	Number of Responses	Percentage
Positive	14	2.8%
Neutral	143	28.6%
Questioning Authority	250	50.0%
Name-calling/Gender insults	90	18.0%
Vicious language	2	0.4%
Hate speech	1	0.2%

Table 6: Breakdown of the Type of Accounts detected among MP May's Tweets

Type of Account	Number of Responses	Percentage
Personal	193	38.6%
Professional	65	13.0%
Bots	1	0.2%
Spammers	1	0.2%
Anonymous	41	8.2%
Suspended/deleted	199	39.8%

either **Personal** users (1.4%) or **Professional** users (0.4%), while **Neutral** Tweets most frequently came from accounts categorized as **Personal** (10.9%), **Professional** (9.4%), and **Suspended/deleted** (7.4%). Tweets coded as **Questioning Authority** were most frequently sent by **Suspended/deleted** users (22.2%), followed by **Personal** users (20.2%), and **Anonymous** users (4.2%). The only instance in which **Bots** and **Spammers** were detected in MP May's sample were when sending Tweets **Questioning Authority**. The Tweets containing **Name-calling/Gender insults** were most frequently sent by users identified as **Suspended/deleted** (8.8%), **Personal** (6.4%), or **Anonymous** (2.6%). Moreover, **Vicious language** identified Tweets were sent by **Suspended/deleted** users (0.2%) and **Anonymous** users (0.2%). There were no identified instances of **Credible threats** and the 1 instance of **Hate speech** was sent by a **Suspended/deleted** account.

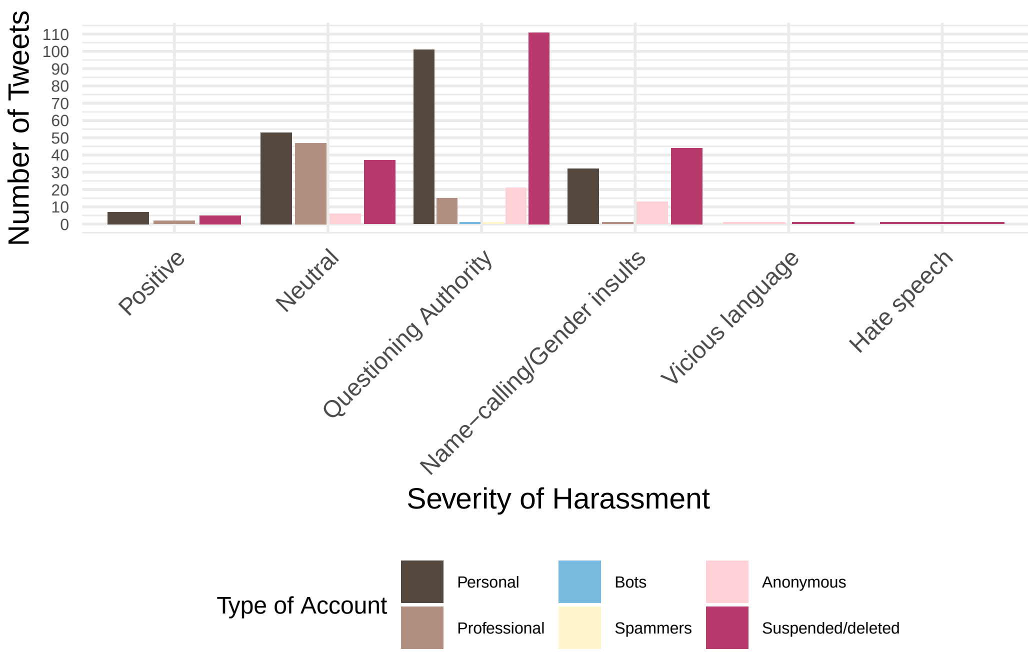

Figure 4: Relationship between Severity of Harassment and Types of Accounts detected among MP May's Tweets

3.5 Laurel Collins

Among this small sample of 13 Tweets sent to MP Collins, 11 (84.6%) were identified as **Neutral** and 2 (15.4%) as **Questioning authority** for `severity of harassment` (see Table 7). No Tweets containing **Positive**, **Name-calling/Gender insults**, **Vicious language**, **Credible threats**, or **Hate speech** were detected in this sample.

For `Type of account`, 9 (69.2%) were detected as **Professional**, 3 (23.1%) as **Personal**,

Table 7: Breakdown of the Severity of Harassment on the seven-point scale detected among MP Collins' Tweets

Severity of Harassment	Number of Responses	Percentage
Neutral	11	84.6%
Questioning Authority	2	15.4%

Table 8: Breakdown of the Types of Accounts detected among MP Collins' Tweets

Type of Account	Number of Responses	Percentage
Personal	3	23.1%
Professional	9	69.2%
Suspended/deleted	1	7.7%

and 1 (7.7%) as **Suspended/deleted** (see Table 8). No **Bots**, **Spammers**, or **Anonymous** accounts were detected in this sample.

The relationship between `severity of harassment` and `types of accounts` present in MP Collins' sample of Tweets is available in Figure 5. **Neutral** Tweets were sent by **Professional** users (61.5%), **Personal** users (15.4%), or **Suspended/deleted** users (7.7%). Tweets **Questioning Authority** were identified as being sent by either **Personal** users (7.7%) or **Professional** users (7.7%). No **Positive**, **Name-calling/Gender insults**, **Vicious language**, **Credible threats**, or **Hate speech** Tweets were detected in this sample and neither were **Bots**, **Spammers**, or **Anonymous** accounts.

4 Model

This trial study aims to evaluate the `severity of harassment` and the `types of accounts` behind the Tweets sent to Canadian female politicians and we are especially interested in seeing the impact of **Suspended/deleted** accounts on the overall severity of harassment of Tweets. The model considers whether an account was suspended or not, as a function of the severity of harassment, and which politician is targeted:

$$\Pr(y_i = 1) = \text{logit}^{-1}\left(\beta_0 + \beta_1 x_i\right) \tag{1}$$

where y_i is the estimated probability whether an account was suspended, x_i is the severity of harassment, and z_i is which politician was targeted.

Our estimates (shown in Figure 6) highlight that there is an estimated 8% probability that Tweets categorized as **Name-calling/Gender insults** were sent by **Suspended/Deleted**

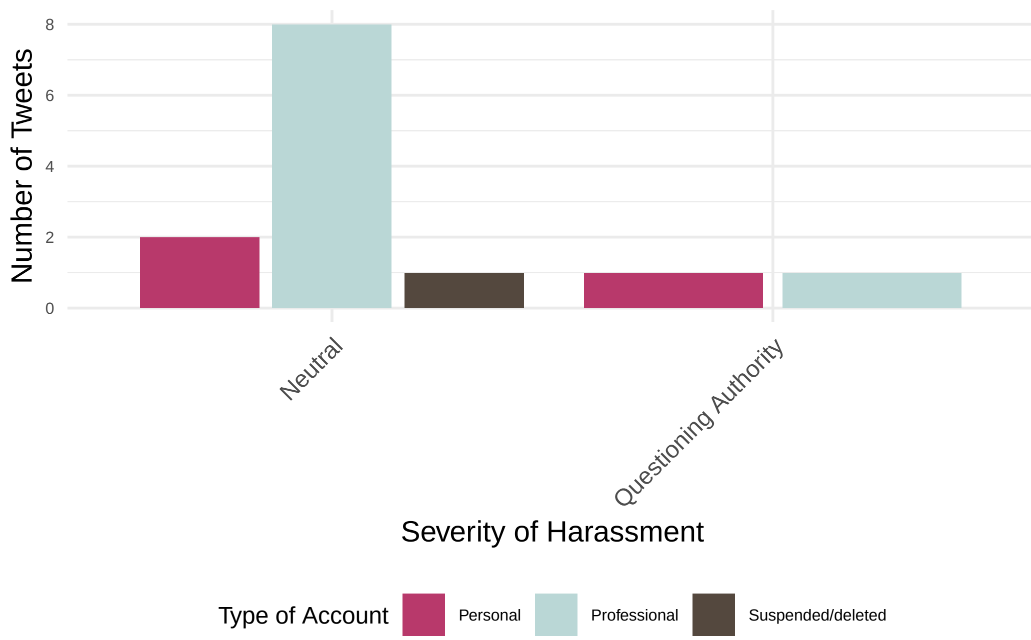

Figure 5: Relationship between Severity of Harassment and Types of Accounts detected among MP Collin's Tweets

users. There is an estimated 93% probability that Tweets coded as **Neutral** were not sent by **Suspended/Deleted** users, while there is an estimated 87% probability that **Positive** Tweets were not sent by **Suspended/Deleted** users. Moreover, our estimates suggest that there is 24% probability that Tweets categorized as **Questioning Authority** were not sent by **Suspended/Deleted** users, while there is 34% probability that Tweets using **Vicious language** were sent by **Suspended/Deleted** accounts.

The model is struggling to offer predictions when the severity of harassment is **Hate speech**. We expect that this is the case because there are only two identified instances of **Hate speech** in our dataset for this trial study, but the number of identified instances is expected to rise in the full-scale version of this study.

The estimates in Figure 6 generally align with our understanding of identified user Tweeting behaviour in this sample of Tweets from MP McKenna and MP May. However, it is interesting that there does not seem to be a particular difference in likelihood that **Suspended/deleted** users were responsible for sending **Positive** (87%) versus **Neutral** (93%) Tweets. I would normally suspect that there would be a higher likelihood that **Positive** Tweets did not come from **Suspended/deleted** users, not the other way around. In future studies, it may be worthwhile to pay closer attention to these two categories and investigate expanding them.

For evaluating which politician was targeted, the model estimates that there is little difference between MP McKenna and MP May. However, there is an estimated 3% probability that MP May is less likely to be targeted by **Suspended/deleted** users, compared to MP McKenna.

Characteristic	**log(OR)**[1]	**95% CI**[1]	**p-value**
severity_of_harassment			
Credible threats	—	—	
Hate speech	14	244, 233	>0.9
Name-calling/Gender insults	0.08	-3.2, 3.3	>0.9
Neutral	-0.93	-4.2, 2.3	0.5
Positive	-0.87	-4.2, 2.5	0.6
Questioning Authority	-0.24	-3.5, 3.0	0.9
Vicious language	0.34	-3.0, 3.7	0.8
name_of_politician			
Catherine McKenna	—	—	
Elizabeth May	-0.03	-0.30, 0.23	0.8

[1]OR = Odds Ratio, CI = Confidence Interval

Figure 6: Examining whether an account was suspended or not, based on the severity of harassment, and which politician was being targeted

Figure 7 investigates whether an account is **Suspended/deleted** primarily based on `severity of harassment`. When **Credible threats** are compared to **Hate speech** there is an estimated 51% probability that **Suspended/deleted** accounts are responsible for the Tweets. For **Vicious language**, there is an estimate 8% probability that **Suspended/deleted** accounts are responsible for the Tweets, compared to **Credible threats**, while there is an estimated 2% probability for Tweets categorized as **Name-calling/Gender insults**. Additionally, when **Credible threats** are compared to **Questioning authority**, there is an estimated 6% probability that **Suspended/deleted** users are not responsible. When comparing **Credible threats** to **Positive** and **Neutral** sentiment in Tweets, there is an estimated 20% probability and 21% probability respectively that **Suspended/deleted** users are less likely to be responsible. Once again, there was essentially no difference between **Positive** and **Neutral** Tweets, which is worthy of further investigation. The model suggests overall that the more severe the sentiment is in Tweets compared to the **Credible threats** category, the more likely a **Suspended/deleted** user is responsible.

We expected a difference between Tweets directed at MP McKenna and MP May (with Tweets sent to MP McKenna containing more harassment), however Figure 7 shows that we were unable to find a quantitative difference. The qualitative differences between MP McKenna and May will be explored in the Discussion section.

Contrast	Estimate	Standard error
Hate speech - Credible threats	0.51	0.36
Name-calling/Gender insults - Credible threats	0.02	0.36
Neutral - Credible threats	-0.21	0.36
Positive - Credible threats	-0.20	0.37
Questioning Authority - Credible threats	-0.06	0.35
Vicious language - Credible threats	0.08	0.38
Elizabeth May - Catherine McKenna	-0.01	0.03

Figure 7: Examining whether an account was suspended or not, based on the severity of harassment, and which politician was being targeted

5 Discussion

Overall, the data from this trial study reveals some form of harassment is present in over two-thirds of the Tweets sent to MP McKenna, MP May, and MP Collins which explicitly discuss climate change (see Table 1). The `severity of harassment` and `type of accounts` behind the Tweets varies by female politician, with some of the main differences in the severity of harassment detected between MP McKenna and MP May being qualitative in nature. The following sections will further discuss these identified trends and compared them to the characteristics of what constitutes a healthy deliberative democracy.

5.1 Severity of Harassment

As hypothesized, the `severity of harassment` detected in Tweets for this trial study varies on the seven-point scale, with at least one Tweet being detected for each category (see Table 1).

I also hypothesized that harassing Tweets were more likely to be categorized as **Questioning Authority**, **Name-calling/gender insults**, and/or **Vicious language**. My hypothesis was two-thirds correct, with 51.5% of Tweets being coded as **Questioning Authority** and 24.0% coded as **Name-calling/gender insults**. However, only 1.2% of Tweets were categorized as **Vicious language**, with **Neutral** (at 20.5%) being the third most identified level in this trial study (further details available in Table 1). Although this hypothesis was not entirely validated through this trial study, I anticipate it being proven in the full-scale version of this study for reasons explained below.

The discrepancy between the number of Tweets identified as containing **Vicious language** and **Neutral** sentiments can be explain by a few factors. Firstly, stronger content moderation processes were applied to content on Twitter prior to Elon Musk's purchase of the platform in 2022, leading to Tweets with more profanities being removed at a higher rate, which will likely

Table 9: Breakdown of Types of Accounts and Severity of Harassment

Severity of Harassment	Type of Account	Number of Responses	Percent
Questioning Authority	Personal	180	17.8%
Questioning Authority	Suspended/deleted	224	22.1%
Name-calling/Gender insults	Personal	66	6.5%
Name-calling/Gender insults	Suspended/deleted	125	12.3%

change with Musk's promotion of "free speech" in 2023 (Citron 2014). Secondly, I did not anticipate there being as much civil discourse about climate change and environmental policy as there was on/around the accounts of MP May and MP Collins. It is difficult to be certain whether this will be the case in the full-scale version of this study, with the more polarized nature of Canadian politics following the Covid-19 pandemic and MP Collins' raised profile which is often a cause of harassment and more uncivil forms of discourse (Rheault, Rayment, and Musulan 2019).

5.2 Type of Account

As hypothesized, at least one account was identified for each of the six `types of accounts`. **Suspended/deleted** accounts constituted 41.7% of all accounts, followed by **Personal** (32.3%), and **Anonymous** (14.8%) (a full breakdown is available in Table 2). The number of **Personal** accounts approximately aligns with number I anticipated finding in this trial study. However, I did not anticipate as many as 41.7% of Tweets would be authored by **Suspended/deleted** users, which could in part be due to the length of time which has passed since these Tweets were authored and collected (further discussed in Limitations).

Moreover, I suspected that the more severe forms of harassment identified in this trial study would come from **Personal** and **Suspended/deleted accounts**. Given the low number of Tweets containing **Vicious language**, **Credible threats**, and **Hate speech**, this hypothesis will be applied to the results for **Questioning Authority** and **Name-calling/Gender insults**. **Personal** users accounted for 17.8% of the Tweets **Questioning Authority**, while **Suspended/deleted accounts** sent 22.1% of the Tweets. **Personal** accounts were responsible for sending 6.5% of the Tweets containing **Name-calling/Gender insults**, while **Suspended/deleted accounts** sent 12.3% (see Table 9).

5.3 Severity of Harassment, Type of Account & Political Views

As hypothesized, accounts belonging to right-wing, ideologically driven users sent Tweets containing harassing content to the three female politicians. In order to evaluate this hypothesis, I combined the datasets of MP McKenna and MP May and used the `filter` function to select key words such as "Conservative," "PPC", "MAGA", and "#TrudeauMustGo" from users'

Table 10: Breakdown of the Severity of Harassment detected among Tweets sent from users with right-wing views

Severity of Harassment	Number of Tweets	Percentage
Neutral	4	3.5%
Questioning Authority	64	56.1%
Name-calling/Gender insults	45	39.5%
Vicious language	1	0.9%

Table 11: Breakdown of the Type of Accounts detected among users that hold right-wing views

Type of Account	Number of Accounts	Percentage
Personal	32	28.1%
Professional	2	1.8%
Spammers	2	1.8%
Anonymous	13	11.4%
Suspended/deleted	65	57.0%

bios. 114 accounts had information in their bios that emphasized their right-wing political views, keeping in mind the discussion from the Data Limitations section.

Unsurprisingly, Table 10 illustrates that 64 (56.1%) of the Tweets were identified as **Questioning authority**, 45 (39.5%) were **Name-calling/Gender insults**, 4 (3.5%) were **Neutral**, and 1 (0.9%) contained **Vicious language**. No Tweets were coded as **Positive**, **Credible threats**, or **Hate speech** which emphasizes that users with right-wing views consistently felt motivated enough to engage with MP McKenna and MP May on Twitter, but not on either extreme of the seven-point scale, confirming my hypothesis.

Furthermore, we can see in Table 11 the breakdown of the different types of accounts that belong to people with right-wing views. 65 (57.0%) of the accounts are **Suspended/deleted**, while 32 (28.1%) are **Personal**, and 13 (11.4%) are **Anonymous**. 2 (1.8%) of the accounts belong to **Spammers** and similarly, 2 (1.8%) of the accounts are **Professional**. No **Bots** were identified. The high number of **Suspended/deleted** accounts identified somewhat contradicts this specific hypothesis, but generally aligns with other findings from this trial study, especially with **Personal** users being the second most frequently identified type of account for people with right-wing views.

Figure 8 emphasizes the relationship between `Severity of Harassment` and `Type of Account` for users with right-wing, ideologically driven views, broken down by politician. MP McKenna received Tweets more frequently than MP May that were from users with right-wing views that were categorized as **Questioning Authority** (32.5% versus 23.7%) and **Name-calling/Gender insults** (23.7% versus 15.8%). MP McKenna also received 1

Tweet (0.9%) containing **Vicious language**, unlike MP May who received none. In contrast to previous results, MP McKenna received more Tweets than MP May (2.6% vs 0.9%) that were **Neutral** when specifically analysing the political views of users. Overall, this analysis reveals that the networked publics which form around the accounts of MP McKenna and MP May hold right-wing views, deny the existence of climate change, and have free time (often dictated by patriarchal norms) to troll female politicians because their actions as climate leaders do not fit traditional gender roles and conceptions of power (Anshelm and Hultman 2014; Mantilla 2013; Geus et al. 2021).

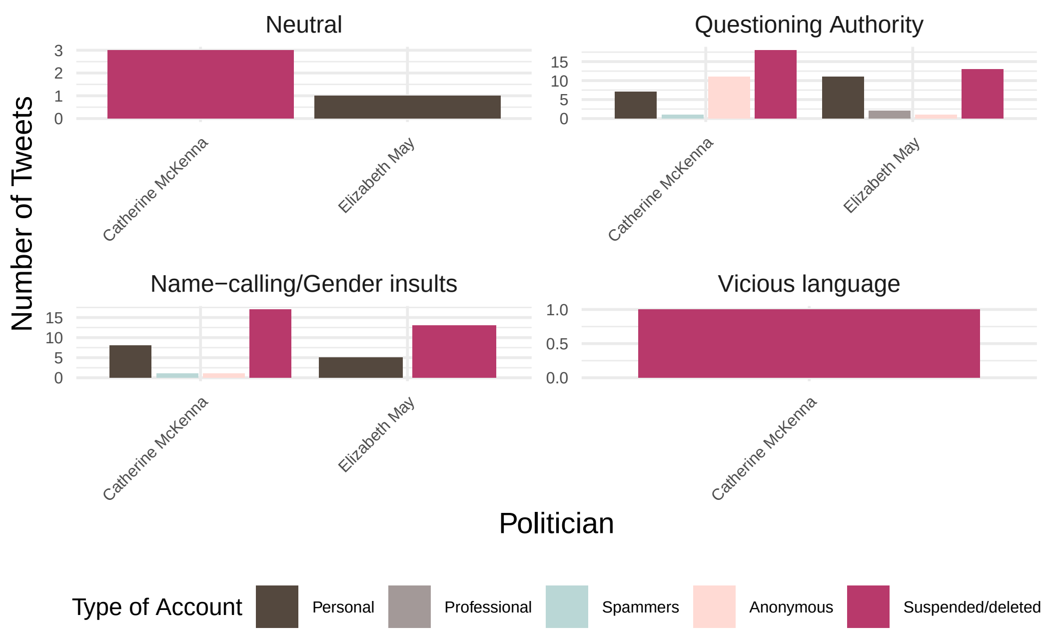

Figure 8: Relationship between Severity of Harassment, Type of Account, and Political Views by politician

5.4 Catherine McKenna

MP McKenna chose not to seek re-election during the 2021 Federal Election and has since returned to private life. Although she cites wanting to help other countries around the world fight climate change as her main reason for leaving, the online and offline harassment she has and continues to face surely impacted her decision. Within the small sample of Tweets used in this trial study, MP McKenna's were found to be the most harassing, with 270 (54%) **questioning her authority** and 153 (30.6%) employing **Name-calling/gender insults** (see Table 3). Among Tweets categorized as **Questioning authority**, many of them questioned her overall competence as a politician and person, not simply on the climate file. 13 Tweets

(2.6%) were found to either contain **Vicious language**, **Credible threats**, or **Hate speech**, which is a larger number then the 10 Tweets (2.0%) that were **Positive**. 54 (10.8%) of the Tweets were determined to be **Neutral** - a much smaller percent than MP May and MP Collins. Figure 8 highlights how MP McKenna receives Tweets with higher levels of harassment from users with right-wing views.

A name which MP McKenna has and continues to be called is *Climate Barbie* (Table 12 provides an example Tweet), so I used the `filter` function to select all Tweets which contained the name to further examine the `severity of harassment` and `type of account`. Figure 9 illustrates that of the 51 Tweets that explicitly use the name *Climate Barbie*, 90.2% were categorized as **Name-calling/Gender insults**, 5.9% as **Vicious language**, and 2.0% for both **Questioning Authority** and **Credible threats**. For the `types of accounts` behind the *Climate Barbie* Tweets, 41.2% are **Suspended/deleted** users, 35.3% are **Anonymous**, 21.6% are **Personal**, and 2.0% are **Spammers** (see Figure 9). These results reveal that the name *Climate Barbie* is often used in derogatory contexts (hence the frequent selection of the **Name-calling/Gender insults** category), but can also be used in more severe ways - represented by the **Vicious language** and **Credible threats** categories. Moreover, the high number of **Anonymous** accounts who employ the name *Climate Barbie* is noteworthy. Given their limited digital footprints, **Anonymous** users likely feel emboldened to use offensive language and derogatory comments and not worry about repercussions.

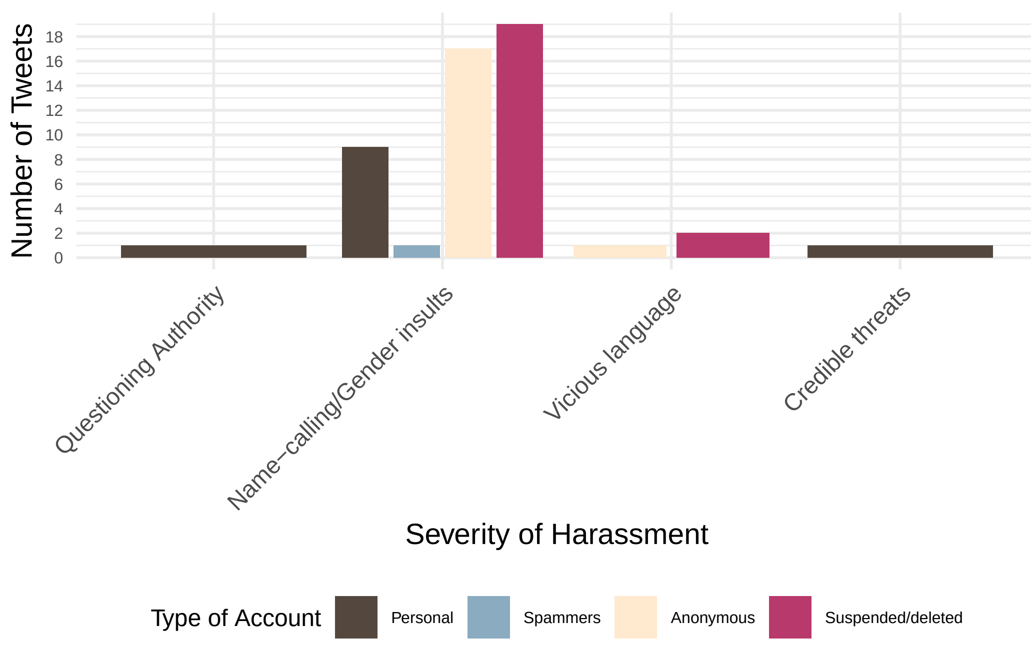

Figure 9: Severity of Harassment and Type of Account identified in Tweets which call MP McKenna *Climate Barbie*

Table 12: Sample of a Tweet containing **Name-calling/Gender insults** sent to MP McKenna by an **Anonymous** account (language redacted for this document).

Tweet
@ cathmckenna "Climate Barbie" is an unhinged Radical Leftist . A climate wh*re turning Tricks for Al Gore

5.5 Elizabeth May

Unlike MP McKenna, the Tweets sent to MP May were more focused on discussing the science and policies surrounding climate change. 28.6% of Tweets sent to MP May were categorized as **Neutral** while 50% the Tweets were **Questioning Authority** (Table 5). While the **Questioning Authority** Tweets still accounted for half of MP May's sample, there were qualitative differences between the way users debated issues with her versus MP McKenna. As observable in Table 13, users question her ability to understand climate science, implement effective policies to stop climate change, and offer up their own approach to solving the problem - undermining her perceived qualifications and power as an elected official. This is in contrast to Tweets sent to MP McKenna which question every aspect of her overall competence, not simply her understanding of climate science. Although there are notable qualitative differences between how users question the authority of both MP McKenna and MP May, users are still questioning the legitimacy and qualifications of the female politicians, with both aspects fitting the definition for the **Questioning Authority** category.

Table 13: Sample of a Tweet **Questioning Authority** sent to MP May from a **Personal** account.

Tweet
@ ElizabethMay Ms May you should be ashamed of your self. More and more science is disputing these dramatic climate emergencies. You are scaring our children and hurting our economy. The climate is changing we cannot stop it but should develop the technolgy and finacial ability to live with it.

5.6 Laurel Collins

Of the 13 Tweets in MP Collins' sample, 11 (84.6%) were **Neutral** in tone, discussing NDP platform commitments and events MP Collins attended on the campaign trail. The other 2 Tweets (15.4%) unsurprisingly **questioned her authority**, a likely harbinger of the severity of harassment that will be detected in the full-scale version of this study (see Table 7). Previous research has found that the higher the profile of female politicians in Canada, the more likely they are to face more severe forms of harassment, which I anticipate will apply to MP Collins (Rheault, Rayment, and Musulan 2019).

5.7 Deliberative Democracy

Referencing previous discussions of the characteristics of what constitutes a healthy deliberative democracy, findings from this trial study will be compared and contrasted to evaluate the extent at which the discourse is healthy for Canadian democracy. Scholars previously noted that democratic legitimacy exists when the public collectively participates in deliberation about consequential topics, while recognizing there are multiple perspectives on every issue, such as climate change (McKay and Tenove 2021; Chen 2017). Through Twitter, the wider Canadian public has the opportunity to add their perspectives to consequential discussions about climate change. Although Twitter is not entirely representative of wider public opinion, it is simply one tool Canadian MPs can employ when trying to glean a general understanding of public opinion (McGregor 2020). Many of the Tweets studied, especially sent to MP May, provided multiple viewpoints on the causes and consequences of climate change, satisfying that aspect of democratic legitimacy (example: Table 13).

In their article, McKay and Tenove (2021) emphasize that maintaining anonymity, especially in the digital public sphere, is a new characteristic of democratic discourse. Only 14.8% of accounts in this trial study were identified as **Anonymous**, but it is likely that users with other types of accounts feel that they can participate in debate in anonymous and pseudonymous ways because of the affordances of Twitter and lack of Canadian legislation governing harmful speech in online spaces (see Table 2). Moreover, **Anonymous** users were the second most frequently identified typed of account that used the phrase *Climate Barbie* to refer to MP McKenna - a derogatory term which undermines healthy democratic discourse and is trend worth looking out for in the full-scale version of this study (see Figure 9).

While the level of debate remained healthy enough for democracy in this trial study, it is anticipated that the Tweets in the full-scale version of this study will be more uncivil, challenging the core values of Canada's deliberative democracy and risking the future of public discourse online and offline about climate change.

5.8 Limitations

The context in which these datasets were initially collected, focusing on mentions the three MPs received, means that my analysis and ability to draw conclusions is especially limited (further discussed in Appendix A). I tried to use these previously collected datasets in this trial study in a nearly identical way to how I will conduct the full-scale version of this study with intentionally created datasets, despite the fact that the old dataset focused on mentions of the MPs and I intended to focus on replies to Tweets authored by the MPs.

MP Collins' lower national profile in 2019 meant that she received far fewer Tweets during the same period as MP McKenna and MP May and that it is challenging to identity patterns and generalize the results from her data. However, I still felt that it was important to include given her increased profile in 2023 and anticipated prominence in the full-scale version of this study. Any of the patterns identified using data from MP McKenna in this trial study will not be usable to directly inform the full-scale version of this study (further discussed Future Research), but more broadly can suggest how to handle data from female Ministers with higher profiles who work on climate change policy issues.

Lastly, Twitter's ever-changing affordances and focuses as a platform (such as promoting "free speech") directly and indirectly impact the severity of harassment deemed acceptable to keep on the platform and the types of accounts worthy of remaining active users. It is impossible to know on a granular level how every change to Twitter affordances impacts each harassing Tweet and account on the platform, but can generally inform hypotheses and patterns established when analysing the data.

5.9 Future Research

Given the changes to Twitter's affordances and the increasingly polarized political climate in Canada following the Covid-19 pandemic, there are multiple aspects of this trial study that will differ in the full-scale version of this study. Since MP McKenna has left public life, Deputy Prime Minister and Minister of Finance Hon. Chrystia Freeland has been selected to replace her as the Liberal politician in full-scale version of this study. MP May briefly handed over leadership of the Green Party of Canada between 2020 and 2022 to Annamie Paul, but has since returned as the Party's Co-Leader with Jonathan Pedneault, meaning her profile and status is largely unchanged between the two versions of this study. Lastly, MP Collins has raised her profile, through her national work as the NDP's Environment Critic and local work as the MP for Victoria, so it is anticipated that there will be more Tweets of hers to analyse and the severity of harassment will fall higher on the seven-point scale.

Some of my approaches, including how `type of account` is determined while coding needs to be refined ahead of the full scale version of this project. My definition of `type of account` in both the introduction of this paper and in my Codebook references the "dynamic" affordances of Twitter, such as the "… interactions and communications between the users" (Singh, Bansal, and Sofat 2018, 383). These dynamics are generally lost and difficult to evaluate in a static dataset, especially when most users have been reduced to a single interaction on the platform. Consequently, I need to determine whether I will solely evaluate users based on their single line in the dataset (discounting the ability to look at how frequently they reply to Tweets for example) or look their profiles up on Twitter as I actively code, potentially risking having more **Suspended/deleted** accounts represented. It will be more challenging to determine if certain users are **Spammers** without looking at how frequently they reply and other interactions they undertake on the platform. The final approach employed will be determined once the dataset for the full-scale study has been collected.

6 Conclusion

In this trial study, I examined Tweets explicitly discussing climate change sent to former MP Catherine McKenna, MP Elizabeth May, and MP Laurel Collins to see the severity of harassment on a seven-point scale and type of accounts behind the Tweets. My study reveals that nearly 80% of Tweets sent to the three MPs contained some level of harassment, with nearly no quantitative differences being identified between Tweets sent to MP McKenna and MP May, although qualitative differences exist. **Suspended/deleted** and **Personal** accounts were most frequently identified as engaging with the female politicians on Twitter and being responsible for sending the more serve forms of harassment identified. The Tweets analysed for this study matched the criteria of what constitutes a healthy deliberative democracy, with users with multiple, diverse viewpoints weighing in on the issue of climate change. In the full-scale version of this study, it is anticipated that Tweets will consistently contain more severe forms of harassment (such as **Vicious language** and **Credible threats**), while still being sent by **Personal** and **Suspended/deleted** accounts. It is crucial to ensure we continue studying and discussing the intersection of climate change denialism and misogyny, because if we cannot mediate the risks of gendertrolling at the highest echelons of power, then female politicians may self-censor and risk everyone's ability to engage in respectful discourse surrounding climate change.

7 Appendix A

This datasheet provides background on who originally collected the raw Twitter data used in this trial study, how it has been previously used, and aims to reveal some of the limitations imposed on this study. The questions below are amended from the ones outlined in Gebru et al. (2021).

7.1 Motivation

1. *For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.*

    - This dataset was created for a group project under the theme "who follows and mentions who during elections" for CMN 4160 - Digital Social Research taught by Professor Elizabeth Dubois at the University of Ottawa.
    - Inessa De Angelis was the group member who led research project design and pitched the idea of selecting former MP Catherine McKenna, MP Elizabeth May, and MP Laurel Collins because of their engagement in climate change policy advocacy.

- Because of her previous work with Catherine McKenna during the 2019 Federal Election campaign, Inessa noticed the connection between climate change denialism, misogyny, and online harassment. After reviewing relevant literature from both Canada and other countries, Inessa noticed a large gap and wanted to help fill the gap through this project and her continued research at the Faculty of Information at the University of Toronto.
- The dataset specifically collected mentions of the three female politicians, not simply replies, which differs from how Inessa will approach the full-scale version of this project. Instead of quantitative content analysis, the group performed social network analysis using Gephi on the datasets.

2. *Who created the dataset (for example, which team, research group) and on behalf of which entity (for example, company, institution, organization)?*
   - Inessa defined the parameters on behalf of her group of what data they wanted collected and Trevor Deley, PhD Candidate in E-Business (supervised by Professor Dubois) collected the data. Both were students at the University of Ottawa.
3. *Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.*
   - Trevor's financial situation during the creation of this dataset is unknown.
   - Inessa's tuition was partially covered by a University of Ottawa Dean's Honour List Merit Scholarship, but there was no direct grant associated with this project.
4. *Any additional comments?*
   - While Inessa has previously worked with former MP Catherine McKenna during the 2019 Federal Election campaign, it is important to note that she did not have access to MP McKenna's social media accounts nor produce social media content, including any of the Tweets in the dataset.

7.2 Composition

1. *What do the instances that comprise the dataset represent (for example, documents, photos, people, countries)?*
   - Each row of the dataset is an individual. However, not every row is a unique individual because some people sent multiple Tweets to the MPs.
2. *How many instances are there in total ?*
   - Between Catherine McKenna, Elizabeth May, and Laurel Collins there were 116,649 Tweets in the raw datasets.

3. *Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (for example, geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not*

    - No, the raw dataset does not contain all the mentions of MPs McKenna, May, and Collins on Twitter leading up to and during the 2019 Federal election campaign but it is also not a sample. Tweets in the dataset range from early August to late October, with the election campaign running from September 11 - October 21, 2019. The missing instances is due to accounts being suspended or deleted from the platform and accounts being set to "private" before data collection happened in early 2021.
    - Given the affordances of Twitter, the sample of Tweets is representative of the nature of discourse about climate policy on Twitter before/during the election campaign because there is diversity in the age, gender, politicial affiliation, and geographic coverage (verified through user bios, locations, and other personal information attatched to their public profiles).

4. *What data does each instance consist of? "Raw" data (for example, unprocessed text or images) or features? In either case, please provide a description.*

    - Each instance contains raw Tweet text and personal account information (that is displayed on their public profile) such as location, bio, username, and display name.

5. *Is there a label or target associated with each instance?*

    - No, there is not.

6. *Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (for example, because it was unavailable).*

    - Yes. Many individuals opted not to list a location on their profile or write a bio, which makes it unavailable and listed as NA in the raw dataset. Not sharing a location or writing a bio could be due to individuals wanting to protect their privacy or not reveal any personal information about themselves.

7. *Are relationships between individual instances made explicit? If so, please describe how these relationships are made explicit.*

    - Yes, each individual instance mentions at least one of the three female politicians of study: former MP McKenna, MP May, or MP Collins and the word "climate" is mentioned somewhere in the Tweet.

8. *Are there recommended data splits (for example, training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.*

    - No.

9. *Are there any errors, sources of noise, or redundancies in the dataset?*

    - It has been over four years since these Tweets were initally sent and over two years since these Tweets were collected for the dataset, so there is potential inaccuracies in reporting which accounts are still on the platform and which have been suspended/deleted.
    - Some users do not have bios or locations indicated (listed as NA), which may impact how coders categorized "type of account".

10. *Is the dataset self-contained, or does it link to or otherwise rely on external resources?*

    - It is self-contained.

11. *Does the dataset contain data that might be considered confidential*

    - No, all data was gathered from publicly available sources.

12. *Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.*

    - Yes, some people may find the nature of the Tweets directed toward the female politicians offensive and harmful, between the vicious language, threats, and climate mis- and dis-information. Viewers are encouraged to take care and seek assistance if required.

13. *Does the dataset identify any sub-populations (for example, by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset*

    - No, the dataset does not have any columns that directly identify any sub-populations, but information regarding gender, location, politicial ideology and party affiliation can be gleaned from the "location" and "bio" columns.

14. *Is it possible to identify individuals (that is, one or more natural persons), either directly or indirectly (that is, in combination with other data) from the dataset?*

    - Yes, some individuals can be identified by their username, display name, profile picture, and bio while others have opted to maintain anonymous profiles.

15. *Does the dataset contain data that might be considered sensitive in any way (for example, data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.*

    - Yes, the dataset contains sensitive information, such as political party affiliation, ideology, and location, however this is public information as users list it in their bio or on the House of Common's website in the instance of the three female politicians.

16. *Any other comments?*

    - No further comments.

7.3 Collection Process

1. *What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated?*

    - Trevor collected these Tweets using a custom Python script to access Twitter's API. The Tweets were also run through Perspective API's sentiment detection software to check for toxicity and assign a score, although Inessa removed these scores during the initial cleaning process for this paper.

2. *What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated?*

    - Tweets were collected via Twitter's API using Python.
    - Inessa is unsure if Trevor employed any validation mechanisms or procedures.

3. *If the dataset is a sample from a larger set, what was the sampling strategy (for example, deterministic, probabilistic with specific sampling probabilities)?*

    - The dataset is not a sample, it contains all the Tweets that were publicly available when Trevor collected the data.

4. *Who was involved in the data collection process (for example, students, crowdworkers, contractors) and how were they compensated (for example, how much were crowdworkers paid)?*

    - Trevor Deley (compensation unknown).

- Professor Elizabeth Dubois (Associate Professor salary from the University of Ottawa, but not directly for this project).
- Inessa De Angelis (no compensation, paid tuition to the University of Ottawa to take CMN 4160).

5. *Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (for example, recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.*
   - Tweets were collected once, in late January/early February 2021 (a specific day/time is unknown).
   - The Tweets included in the dataset were created between the start of August and the end of October of 2019.
6. *Were any ethical review processes conducted (for example, by an institutional review board)?*
   - No.
7. *Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (for example, websites)?*
   - All data was obtained via a third party: Twitter.
8. *Were the individuals in question notified about the data collection?*
   - No.
9. *Did the individuals in question consent to the collection and use of their data?*
   - No.
10. *If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses?*
    - No, consent was never obtained.
11. *Has an analysis of the potential impact of the dataset and its use on data subjects (for example, a data protection impact analysis) been conducted?*
    - No, an analysis of this nature has not been conducted.
12. *Any other comments?*
    - No further comments.

7.4 Cleaning/Labelling

1. *Was any preprocessing/cleaning/labeling of the data done?*

   - It is unknown whether Trevor conducted any cleaning of the raw datasets with Python, beyond obtaining toxicity scores via Perspective API.
   - For this trial study, Inessa used R to clean and simplify column names, remove additional variables, and filter out Tweets which did not contain the word `climate`.

2. *Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (for example, to support unanticipated future uses)?*

   - Yes. Inessa has the original raw datasets saved in her personal Google Drive and on the desktop of her personal Mac.

3. *Is the software that was used to preprocess/clean/label the data available? If so, please provide a link or other access point.*

   - Trevor used Python and Perspective API by Jigsaw. Perspective API is currently free to use but requires registration. Users attempting to use Perspective API may face issues going forward with Twitter limiting access to their API.
   - Inessa uses R.

4. *Any other comments?*

   - No further comments.

7.5 Uses

1. *Has the dataset been used for any tasks already? If so, please provide a description*

   - Yes. This dataset was used for the aforementioned CMN 4160 class project.
   - We used Gephi to conduct social network analysis to see which communities formed around the Tweets and Twitter accounts of former MP Catherine McKenna, MP Elizabeth May, and MP Laurel Collins. We found that McKenna had 26 communities, May had 131 communities, and Collins had 18. We also found that harssment was sent by users with personal accounts and was most likely to show up in the same community as the three female politicans. These findings were written up in a professional-style guide, aimed at women running for office. This project report was used by Professor Dubois as an example for future students in her class, but not publicly distributed beyond the class' Brightspace page.

2. *Is there a repository that links to any or all papers or systems that use the dataset?*

- No.

3. *What (other) tasks could the dataset be used for?*

   - Beyond this trial study, this dataset could be used to see the amount of discourse about other policy issues that mattered before/during the 2019 Federal election, such as the economy and housing.

4. *Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (for example, stereotyping, quality of service issues) or other risks or harms (for example, legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms?*

   - No.

5. *Are there tasks for which the data set should not be used? If so, please provide a description.*

   - This dataset (and any Twitter data generally) should not be used to measure public opinion, as it is not representative of the general Canadian public.

6. *Any other comments?*

   - No further comments.

7.6 Distribution

1. *Will the dataset be distributed to third parties outside of the entity (for example, company, institution, organization) on behalf of which the dataset was created?*

   - No. Due to Twitter's policies about sharing data, this dataset is not publicly available but can be obtained by contacting Inessa De Angelis (inessa.deangelis@mail.utoronto.ca). Twitter's policies outline that datasets are not to be uploaded to GitHub or similar sites/repositories without removing all identifying information and only including the Tweet ID or User ID.

2. *How will the dataset be distributed (for example, tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?*

   - No, this dataset will not be distributed and does not have a DOI.

3. *When will the dataset be distributed?*

- The dataset is currently available. Please contact Inessa via email to access it.

4. *Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?*

    - No.

5. *Have any third parties imposed IP-based or other restrictions on the data associated with the instances?*

    - No restrictions are known.

6. *Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?*

    - No restrictions are known.

7. *Any other comments?*

    - No further comments.

7.7 Maintenance

1. *Who will be supporting/hosting/maintaining the dataset? How can the owner/curator/manager of the dataset be contacted?*

    - There is no regular maintaince of this dataset, but Inessa De Angelis is responsible.
    - She can be reached via email at inessa.deangelis@mail.utoronto.ca.

8 Appendix B

The coding form is available here: https://forms.gle/ryyv4YFKKmpfTs4c6

8.1 Form Preamble

This is the coding form for the Torrential Twitter Trial Study. Please refer to the Codebook (available in the GitHub repository for this project under Inputs –> Codebook) while coding Tweets.

Please contact inessa.deangelis@mail.utoronto.ca if you have questions or require any further information.

8.2 Form Questions

(1) Coder name

- Inessa

(2) Name of Politician

- Catherine McKenna
- Elizabeth May
- Laurel Collins

(3) Tweet URL

- (short text answer)

(4) Tweet text

- (long text answer)

(5) Username

- (short text answer)

(6) Name

- (short text answer)

(7) Bio

- (long text answer)

(8) Severity of harassment

- 1
- 2
- 3
- 4
- 5
- 6
- 7

(9) Type of account

- 1
- 2
- 3
- 4
- 5
- 6

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