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

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Research has shown that women in politics face considerable harassment. Known as "gendertrolling," this harassment is part of a global trend of violence against women in politics. This study investigates the severity of harassment three Canadian female politicians receive when Tweeting about climate change and the types of accounts behind the replies. Results from the quantitative content analysis reveal that 86% of Tweets contained some form of harassment. I then built a Bayesian hierarchical model to investigate the relationship between the severity of harassment and the type of account that a user has. The results from my model suggest that despite differences in political affiliation and status, the three politicians are equally impacted by harassment when Tweeting about climate change. *This paper contains language and themes that some readers may find offensive.*

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*Code and select data available at: https://github.com/InessaDeAngelis/torrential_twitter_bell_conf

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1 Introduction

"F*CK OFF WITH YOUR CLIMATE SCAM .. nazi traitor b!tch," reads a reply sent to a Tweet about climate change that originated on the account of Canada's Deputy Prime Minister (DPM) and Minister of Finance, the Honourable Chrystia Freeland. For DPM Freeland and women across all political parties and levels of government in Canada and other democratic nations, coping with online and offline harassment is a reality of serving as an elected official (Nadim & Fladmoe, 2021; Southern & 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" (Anshelm & Hultman, 2014; Citron, 2014; Vickery & Everbach, 2018). 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 & Connor Green, 2020; de Geus et al., 2021; Rheault et al., 2019).

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 DPM and MP for University–Rosedale, Hon. Chrystia Freeland (from the Liberal Party), MP for Saanich–Gulf Islands, Elizabeth May (Co-Leader of the Green Party), and MP for Victoria, Laurel Collins (from the New Democratic Party) receive specifically when Tweeting about climate change and environmental policy on a seven-point scale and investigate the types of accounts behind the Tweets on a six-point scale. After manually coding Tweets to determine the severity of harassment and type of account, I then built a Bayesian hierarchical model to explore the relationship between the type of account, whether a user was verified through Twitter's subscription program, and which female politician the reply was directed toward to see whether certain combinations of these variables are more likely to lead to a reply which contains harassment. It is hypothesized that evidence of harassment will be detected in the replies and that Personal and Anonymous Twitter accounts belonging to right-wing and ideologically-driven users will send Tweets containing the most harassment to the female politicians.

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 et al., 2018; Uddin et al., 2014). Types of accounts include:

1. Personal
2. Professional
3. Bots
4. Spammers
5. Anonymous
6. Suspended/deleted

My analysis reveals that 86% of all replies to Tweets about climate change and environmental policy that originated on the accounts of DPM Freeland, MP May, and MP Collins contain some form of harassment, ranging from Questioning authority to Hate speech. The remaining 14% of Tweets had either positive or neutral sentiments. Questioning the authority of female politicians, followed by Name-calling/Gender insults were the most common forms of harassment identified, accounting for over 80% of all Tweets. Harassing Tweets were most likely to be sent by Spammers or Anonymous accounts. My Bayesian hierarchical model suggests that there are no significant quantitative differences between the severity of harassment received by the three politicians, although qualitative differences, including word choices and tone were detected during the coding process. My Discussion section further explores these qualitative and quantitative differences, among other key findings.

In the remainder of this paper, I commence with the Literature Review, followed by my Theoretical Framework. Next, I discuss my Data and Methods. Then, I highlight my Results and Model, before providing further analysis and insights in the Discussion section. Finally, in the Conclusion, I summarize my main findings.

2 Literature Review

2.1 Twitter & The Digital Public Sphere

The notion of having a public sphere for political deliberation is as old as Athenian democracy itself (Papacharissi, 2002). In its simplest form, the public sphere is a place where "…society engages in critical public debate" (Habermas, 1989, p. 52) and meaning is "…generated, circulated, contested, and reconstructed" (Fraser, 1995, p. 287). Although Jürgen Habermas wrote about the public sphere in the mid-twentieth century, eighteenth century bourgeois society served as the basis for his theory, overlooking how elites tried to influence and dominate the form political discourse took among other socio-economic classes (Megarry, 2014; Vickery & Everbach, 2018). Through Habermas' conceptualization, the public sphere intends to magnify the voices of the political elites (traditionally white men), while diminishing and even vilifying the voices of minorities – traits which have been transposed into the digital public sphere (Vickery & Everbach, 2018).

The past few decades have led to the structural transformation and fragmentation of the public sphere, moving from having a singular, "official" public sphere to a multitude of parallel smaller ones, called "subaltern counterpublics" and networked publics mediated by technological affordances (boyd, 2010; Bruns & Highfield, 2015; Fraser, 1991). Technology reorganized the flow of information in society, distinguishing networked publics from subaltern counterpublics and the "official" public. Discourse traditionally happened in mediated spaces, but the rise of social media allows it to happen everywhere, theoretically breaking down barriers of who has access to the walled garden of democratic discourse (Trifiro et al., 2021; Vickery & Everbach, 2018). Despite the potential for the formation of new publics online, including issue publics driven by shared policy interests such as climate change, the leading voices in networked publics largely continue to be white, male, Christian, and have free time (often dictated by patriarchal norms) to actively contribute to discussions (Bruns, 2023; de Geus et al., 2021; Mantilla, 2013). Networked publics use trolling and harassment to undermine the authority of female politicians whose actions do not fit traditional gender roles and conceptions of power (de Geus et al., 2021; Mantilla, 2015; Megarry, 2014). Consequently, women have and continue to be on the margins of the public sphere, both in physical spaces like the House of Commons and online, as underscored by an Inter-Parliamentary Union (2022) global survey which found that 82% of female politicians reported being subjected to psychological violence (including harassment, threats, and sexist comments). In Canada, specific examples of on-going marginalization can be seen through the lived experiences of women in politics, with only one female Prime Minister to date (the Rt. Hon. Kim Campbell) and 30% of federal MPs being female (de Geus et al., 2021; House of Commons, 2024).

The original mindset for the development of the internet in the second half of the twentieth century was one of utopianism and democratic renewal – a new space for civil conversations (Papacharissi, 2002, 2004). However, early 2000s political communication theorists often overlooked the aims and agendas of the people who engineered these technologies (Papacharissi, 2004). Megarry (2020) adds that the internet was seen as the "last frontier" for male domination, much like the classic image of the American Wild West. The behaviours and norms of the Wild West continue to play out through the actions of male tech CEOs, such as Elon Musk, and through the way platforms are governed. While often lacking in application, social media platforms including Twitter have slowly adopted rigorous content moderation and community safety policies (Reepschlager & Dubois, 2021).

2.2 Harassment of Women in Politics

Gender-based harassment and gendertrolling on Twitter is well-documented in the literature (Carlson, 2021; Mantilla, 2013; Trifiro et al., 2021; Vickery & Everbach, 2018). Previous research has started distinguishing traits of harassment based on a politician's status and visibility in politics and across traditional and social media. Blatant harassment is most likely to impact politicians of higher status and visibility, such as Cabinet Ministers (Rheault et al., 2019), while harassment of backbench MPs is often through more subtle, everyday microaggressions (Harmer & Southern, 2021). Both Collignon & Rüdig (2020) and Erikson et al. (2023) found that the intersection between a politician's age, gender, and political affiliation largely determines the type and frequency of harassment they face, leading to younger, female politicians more frequently receiving harassing messages than older politicians. Widespread and systematic harassment threatens meaningful political participation by women, the nature of policy debates in the House of Commons, and the future of democracy (de Geus et al., 2021; Southern & Harmer, 2021). While it is difficult to know precisely which combination of characteristics contribute to the intensity of harassment in the digital public sphere, harassment continues to be used as an equalizing force to silence the voices of women and maintain the status quo (Mantilla, 2015; McCright & Dunlap, 2011).

3 Theoretical Framework

By employing the theory of deliberative democracy, this paper analyzes responses to Tweets sent by female politicians which explicitly discuss climate change and environmental policy to evaluate the extent at which they fulfill the characteristics of healthy democratic discourse. Often paired with their work on the public sphere, Jürgen Habermas and Richard Sennet are credited for publishing founding research on the theory of deliberative democracy (Kies, 2010). Recently, communication and media studies scholars have reconceptualized the formation of the public sphere, evaluating the role of platforms with promised democratizing qualities, disinformation, and how these mediums impact the original notion of deliberative democracy (Bruns, 2023).

At its core, deliberative democracy "is a normative theory of democratic legitimacy based on the idea that those affected by a collective decision have the right, opportunity, and capacity to participate in consequential deliberation about the content of decisions" (Ercan et al., 2019, p. 23). Democratic legitimacy is established by allowing the public to collectively participate in respectful and reasonable deliberation about consequential decisions, while recognizing that there are multiple viewpoints on every issue (Chen, 2017; McKay & Tenove, 2021; Pain & Masullo Chen, 2019). McKay & Tenove (2021) highlight that a new characteristic of deliberative democracy is the ability for those who participate in debate to do so in anonymous and pseudonymous ways, which both strengthen and undermine deliberation in different ways.

Diverging scholarly viewpoints exist when operationalizing and applying the theory of deliberative democracy. Some scholars view the theory in rigid terms, evaluating all characteristics and scenarios, such as political parties, systems, and institutions on a "yes" or "no" basis (Sokolon, 2019). However, as Rossini (2022) suggests, the theory of deliberative democracy can be viewed on a scale – looking at the extent in which healthy democratic speech exists in specific contexts. In our increasingly digitized democracy, we cannot overlook or discount how algorithms and platform affordances are building the networks and contexts in which influential democratic deliberation takes place (Bruns, 2023).

In this paper, I adopt a "to what extent" perspective. This perspective aligns with the seven-point scale I developed to measure the severity of harassment on the basis that democratic discourse is nuanced and relies both on traditional democratic theory and contemporary approaches to media studies (Bruns, 2023). This approach recognizes that shades of civil and uncivil speech simultaneously exist in the digital public sphere. Furthermore, I assume the perspective that to some degree, healthy disagreement is accepted and needed (aligning with Rossini (2022)), but not to the extent of female politicians self-censoring out of fear for their physical and psychological safety. Results from my data analysis and model will be evaluated, using the aforementioned definition and characteristics of deliberative democracy, to see the extent in which the discourse among the Tweets in my dataset can be considered healthy for Canadian democracy.

4 Data and Methods

4.1 Data Collection

All Twitter data was collected throughout the month of October 2023 using the statistical programming software R (R Core Team, 2023) and functions from `voson.tcn` (Gertzel, 2021) and the `tidyverse` (Wickham et al., 2019). Paid access to Twitter's Basic v2 Application Programming Interface (API) endpoint was obtained before using the advanced search feature to determine which Tweets I wanted to download via the API. My sample includes any original Tweets written in English (no quote or Retweets) that originated on the accounts of DPM Freeland (@cafreeland), MP May (@elizabethmay), and MP Collins (@laurel_bc) that were posted between September 1, 2022, and October 31, 2023. Tweets also had to the contain the word "climate," "environment," and/or "environmental" (as part of the text of the Tweet or as a hashtag). For threaded Tweets sent by the politicians, the first Tweet of the thread had to contain at least one of the key words and the overall focus of the thread had to be on climate change and/or environmental policy. For Tweet threads that mentioned one of the key words in later Tweets and in passing, these Tweets and replies were omitted due to their lack of relevance. Key words were also checked for applicability, given the use of words such as "climate" and "environment" to reference geopolitics and economic situations and not actual climate or environmental policy. Within the parameters of the sample, DPM Freeland's Tweets were from October 2022 to October 2023 and had either the key word "climate" or

Table 1: Number of replies and their overall percentage of the sample by female politician following the data cleaning process

Name of Politician	Number of Replies	Percentage
Chrystia Freeland	2400	58%
Elizabeth May	1058	26%
Laurel Collins	681	16%

"environment". MP May's Tweets were from September 2022 to October 2023 and included the words "climate," "environment," and "environmental". Lastly, MP Collins' Tweets were from October 2022 to October 2023 and included the words "climate," "environment," and "environmental."

I ultimately collected 11 original Tweets from DPM Freeland, 32 original Tweets from MP May, and 25 original Tweets from MP Collins. Between all the original Tweets and replies, there were 2,424 Tweets for DPM Freeland, 1,094 Tweets for MP May, and 711 Tweets for MP Collins for a total of 4,229, before cleaning the datasets. The distribution of the number of original Tweets and associated replies was anticipated, given Rheault et al. (2019) finding that status and visibility impact the quantity of harassment faced by Canadian politicians.

4.2 Data Cleaning

4.2.1 Raw Data

The raw datasets underwent multiple cleaning procedures and tests before being ready to manually code. Cleaning refers to the process of preparing a raw dataset for further analysis, ensuring basic aspects like each Tweet and corresponding account metadata has its own column, row, and cell, before moving onto project-specific preparations (Alexander, 2023). Cleaning serves as a useful process for identifying anomalies in the dataset, such as mis-matched Tweets and account metadata. The `voson.tcn` package provided several columns of Twitter metadata that was not relevant to the objectives of this paper, so I eliminated those and focused on columns such as the text of the Tweet, the user's location, bio, profile picture, and whether they paid to be verified with a blue checkmark through Twitter's subscription program. All raw and coded data cleaning was done using R (R Core Team, 2023), utilizing functions from the `tidyverse` (Wickham et al., 2019) and `janitor` (Firke, 2023). The original Tweets and replies sent by the female politicians in response to their own thread (known as a threaded Tweet) were omitted during the cleaning process. The few replies sent in languages other than English, including French, Ukrainian, German, and Arabic were removed. Testing of the combined and cleaned datasets was conducted using `validate` (Van der Loo et al., 2023) before being manually coded. The final number of Tweets left following these cleaning procedures are displayed in Table 1, which highlights that DPM Freeland is overrepresented in my sample.

4.2.2 Coded Data

After manually coding the 4,139 Tweets using my Codebook (see Appendix), I proceeded to the second round of cleaning. I eliminated columns of data which were useful for determining the type of account but not relevant for the next steps of my analysis. 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. Furthermore, 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 `validate` (Van der Loo et al., 2023), primarily validating variable types and ensuring the number of rows in the dataset matches the number of Tweets I coded. I then analyzed and visualized my data using functions from `knitr` (Xie, 2014), `kableExtra` (Zhu, 2021), `Formattable` (Ren & Russell, 2021), and `ggplot2` (Wickham, 2016).

4.3 Data Coding

4.3.1 Codebook

I developed a comprehensive codebook building on previous research and a sample of Tweets (see Appendix). Severity of harassment is coded on a seven-point scale, with the seven categories being: Positive, Neutral, Questioning authority, Name-calling/Gender insults, Vicious language, Credible threats, and Hate speech. There is agreement among scholars from fields such as communication and media studies, women and gender studies, and political science that there are no universal definition or ways of measuring and characterizing severity of harassment, incivility, and hate speech (Krook, 2020; Mantilla, 2015; Tenove et al., 2023). Through this study, I develop and test a new quantitative seven-point scale which contributes to on-going research by emphasizing everyday forms of harassment, such as microaggressions and questioning the authority of female politicians. These more everyday forms of harassment are often missed during binary coding conducted by large language models (LLMs). My seven-point scale also combines the nuance from previous qualitative projects which employ content analysis and interviews, while recognizing the benefits of more statistical and quantitative approaches offered by computational political communication researchers.

4.4 Data Limitations

Twitter, the platform's affordances, and the types of accounts and content circulating is ever-changing. A major limitation of using Twitter data for any research is the inability to determine a representative sample of voting-age Canadians and draw generalizable results about public opinion on any given issue (Bermingham & 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, p. 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 & Hellsten, 2015). Due to the global and open nature of social media platforms, some of the Tweets captured are from users who claim to be in the United States, the United Kingdom, and Australia, therefore limiting our ability to solely see the behaviours of Canadian users.

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 users' 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 & 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.

There are several restrictions placed on the storage and sharing of data collected via Twitter's API, limiting the reproducibility of this research project (Alexander, 2023; Twitter Developer, 2023). Datasets, even if personally identifying information such as usernames and locations have been removed, cannot be uploaded to open source platforms like GitHub. While advancing our understanding of the harassment faced online by Canadian female politicians, I am ensuring that proper steps are taken to not further victimize female politicians through ethical data storage and analysis (Krook, 2020).

5 Results

5.1 Severity of Harassment

Among the 4,139 Tweets from the three female politicians, 2,284 (55%) were identified as Questioning authority, 1,060 (26%) as Name calling/Gender insults, and 542 (13%) as Neutral (see Table 2). 144 (3%) contained Vicious language, while Positive, Credible threats, and Hate speech all respectively accounted for 1% of the Tweets detected. For all three politicians, the most frequently selected categories are Questioning authority, followed by Name-calling/Gender insults, and Neutral.

Table 2: Breakdown of Severity of Harassment on the seven-point scale detected in Tweets to all three politicians

Severity of Harassment	Number of Replies	Percentage
Positive	44	1%
Neutral	542	13%
Questioning Authority	2284	55%
Name-calling/Gender insults	1060	26%
Vicious language	144	3%
Credible threats	33	1%
Hate speech	32	1%

Table 3: Breakdown of Type of Accounts detected in replies to all three female politicians

Type of Account	Number of Accounts	Percentage
Personal	802	19%
Professional	45	1%
Bots	10	0%
Spammers	1701	41%
Anonymous	1515	37%
Suspended/deleted	66	2%

5.2 Type of Account

Table 3 summarizes the distribution of types of accounts identified. Spammers accounted for 1,071 (41%) of all accounts, followed by 1,515 (37%) Anonymous accounts, and 802 (19%) Personal accounts. Small numbers of accounts categorized as Suspended/deleted (2%), Professional (1%), and Bots (0%) were detected, which will be further examined in Discussion and Limitations. While some users sent multiple replies to either one, two, or all of the female politicians, over 75% of users only appeared once in the dataset, aligning with previous results from Theocharis et al. (2020) and Ward & McLoughlin (2020).

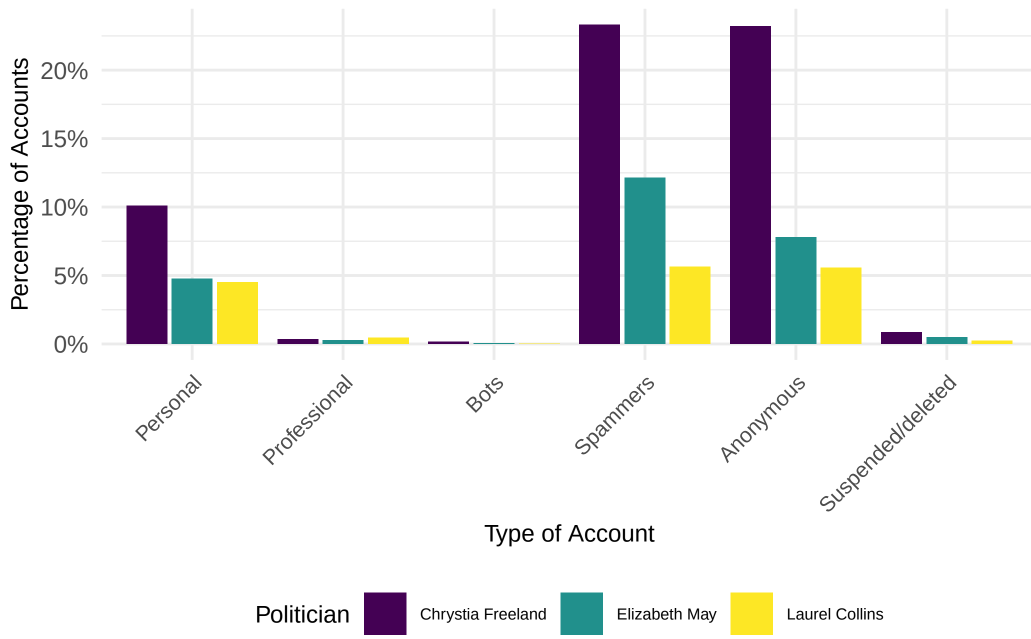

Figure 1: Type of Accounts behind the Tweets received, broken down by politician

5.3 Chrystia Freeland

For DPM Freeland, 1,189 (50%) of her Tweets were categorized as Questioning authority, followed by Name-calling/Gender insults with 678 (28%), and 356 (15%) Neutral Tweets (see Table 4). 99 (4%) of her Tweets contained Vicious language, with the remaining categories of Positive, Credible threats, and Hate speech each accounting for 1% of the total Tweets. The fewest number of Tweets in DPM Freeland's sample were categorized as Positive, with Hate speech being more prominent, which illustrates the increasingly toxic nature of discourse directed at DPM Freeland.

Table 4: Breakdown of the Severity of Harassment on the seven-point scale detected among DPM Freeland's Tweets

Severity of Harassment	Number of Accounts	Percentage
Positive	19	1%
Neutral	356	15%
Questioning Authority	1189	50%
Name-calling/Gender insults	678	28%
Vicious language	99	4%
Credible threats	30	1%
Hate speech	29	1%

Table 5: Breakdown of the Types of Accounts detected among DPM Freeland's Tweets

Type of Account	Number of Accounts	Percentage
Personal	418	17%
Professional	14	1%
Bots	7	0%
Spammers	965	40%
Anonymous	961	40%
Suspended/deleted	35	1%

As illustrated by Table 5, Spammers and Anonymous accounts made up 80% of all identified accounts, followed by 418 (17%) Personal accounts. Very small numbers of Professional, Bots, and Suspended/deleted accounts were detected.

For DPM Freeland, the relationship between severity of harassment and type of account can be seen in Figure 2. Positive and Neutral Tweets were most frequently sent by Personal accounts, while Tweets Questioning authority and Name-calling/Gender insult most frequently came from Anonymous accounts, closely followed by Spammers. Anonymous accounts, closely followed by Spammers, were responsible for sending the most Tweets containing Vicious language, while Credible threats and Hate speech were most often sent by Spammers.

5.4 Elizabeth May

Among the sample of MP May's Tweets, 583 (55%) were categorized as Questioning authority, 295 (28%) as Name-calling/Gender insults, and 133 (13%) as Neutral (details in Table 6). 12 (1%) of the Tweets in MP May's sample were Positive, with 1 (0%) Tweet belonging to both the Credible threats and Hate speech categories.

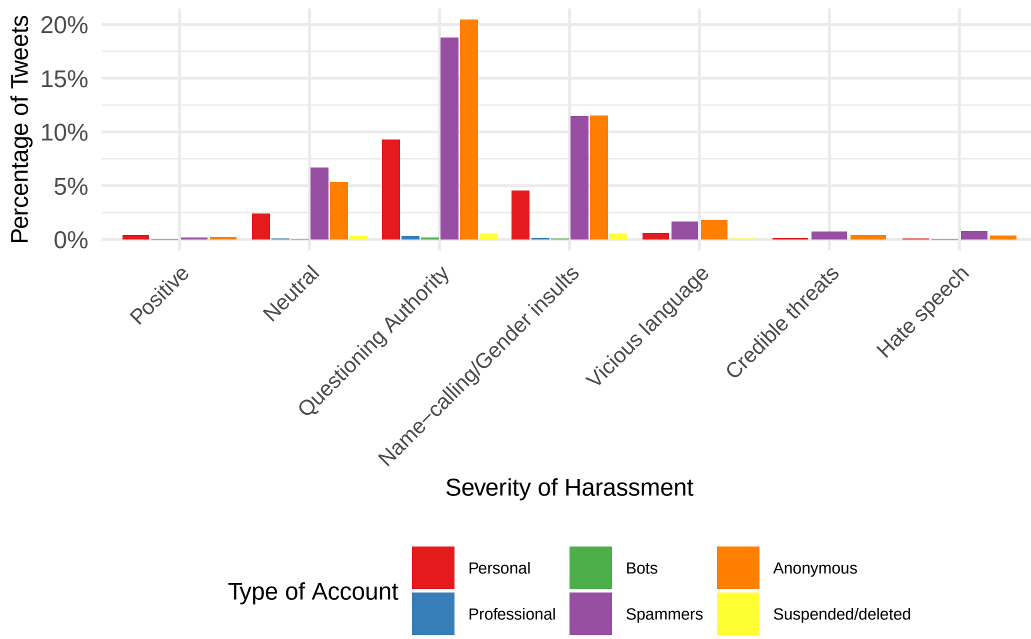

Figure 2: Relationship between Severity of Harassment and Types of Accounts detected among DPM Freeland's Tweets

Table 6: Breakdown of the Severity of Harassment on the seven-point scale detected among MP May's Tweets

Severity of Harassment	Number of Accounts	Percentage
Positive	12	1%
Neutral	133	13%
Questioning Authority	583	55%
Name-calling/Gender insults	295	28%
Vicious language	33	3%
Credible threats	1	0%
Hate speech	1	0%

Table 7: Breakdown of the Types of Accounts detected among MP May's Tweets

Type of Account	Number of Accounts	Percentage
Personal	198	19%
Professional	12	1%
Bots	2	0%
Spammers	502	47%
Anonymous	323	31%
Suspended/deleted	21	2%

Table 8: Breakdown of the Severity of Harassment on the seven-point scale detected among MP Collins' Tweets

Severity of Harassment	Number of Accounts	Percentage
Positive	13	2%
Neutral	53	8%
Questioning Authority	512	75%
Name-calling/Gender insults	87	13%
Vicious language	12	2%
Credible threats	2	0%
Hate speech	2	0%

Table 7 emphasizes that 502 (47%) of the accounts in MP May's sample belong to Spammers, followed by 323 (31%) Anonymous accounts, and 198 (19%) Personal accounts. Moreover, 21 (2%) of accounts in MP May's sample are Suspended/deleted, 12 (1%) Professional, and 2 (0%) Bots.

The relationship between severity of harassment and type of account in Tweets sent to MP May can be seen in Figure 3. Positive and Neutral Tweets most frequently were sent by Personal accounts, while Tweets Questioning authority and Name-calling/Gender insult most frequently came from Spammers. Anonymous accounts were responsible for sending the most Tweets containing Vicious language, while Credible threats were only sent by Anonymous accounts and Hate speech was only sent by Spammers.

5.5 Laurel Collins

Of the Tweets in MP Collins' sample, 512 (75%) were categorized as Questioning authority, 87 (13%) as Name-calling/Gender insults, and 53 (8%) as Neutral. As shown in Table 8, the remaining Tweets were categorized as Positive (13 or 2%), Vicious language (12 or 2%), Credible threats and Hate speech (2 Tweets per category or 0%).

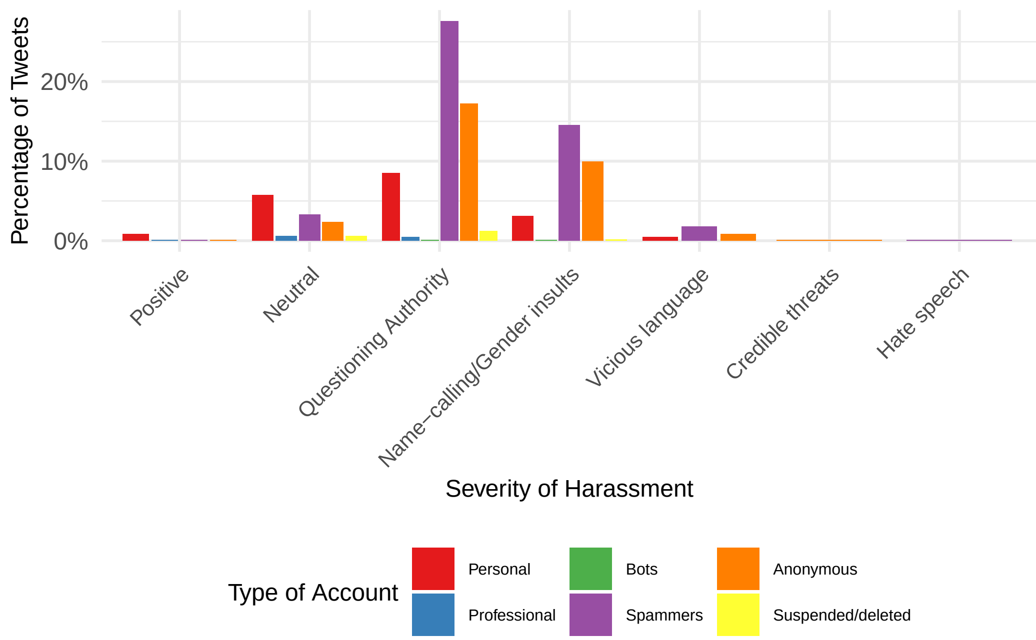

Figure 3: Relationship between Severity of Harassment and Types of Accounts detected among MP May's Tweets

For MP Collins, 68% of the accounts were categorized as both Spammers and Anonymous, followed by Personal (186 or 27%). As seen in Table 9, the remaining accounts were categorized as Professional (19 or 3%), Suspended/deleted (10 or 1%), and Bots (1 or 0%).

Figure 4 emphasizes the relationship between severity of harassment and type of account. Positive, Neutral, and Credible threats Tweets were most frequently sent by Personal accounts, while Tweets Questioning authority and Name-calling/gender insults most frequently came from Spammers, closely followed by Anonymous accounts. Additionally, Anonymous accounts were responsible for sending the most Tweets containing Vicious language, while Hate speech was equally sent by Spammers and Anonymous accounts.

6 Model

I am interested in seeing why some Twitter users are more predisposed than others to send harassing Tweets to Canadian female politicians. In particular, I want to further investigate the combination of the type of account a user has, whether they are verified, and which politician they are replying to in order to predict if they are more likely to send a harassing Tweet. Historically, accounts with the blue checkmark/tick were regarded as credible individuals and/or organizations, sharing legitimate information (Haman & Školník, 2023). However, since Musk

Table 9: Breakdown of the Types of Accounts detected among MP Collins' Tweets

Type of Account	Number of Accounts	Percentage
Personal	186	27%
Professional	19	3%
Bots	1	0%
Spammers	234	34%
Anonymous	231	34%
Suspended/deleted	10	1%

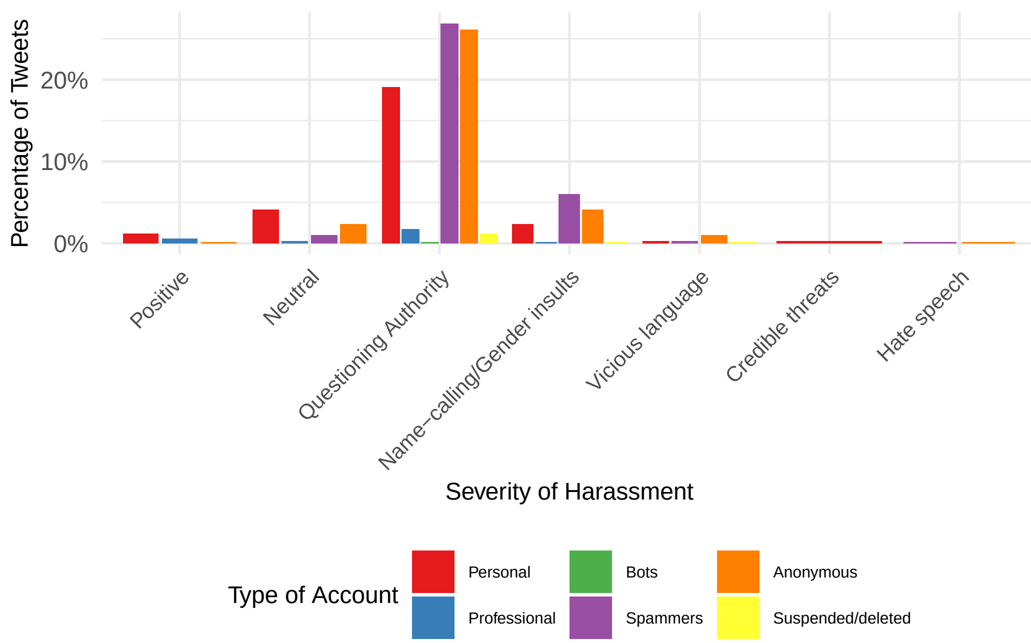

Figure 4: Relationship between Severity of Harassment and Types of Accounts detected among MP Collins' Tweets

introduced changes to Twitter's verification policy in April 2023, the Center for Countering Digital Hate (2023) found that 99% of online hate was spread by malicious users who paid to be verified, allowing for circumvention of content moderation rules. Bayesian hierarchical modeling using the statistical programming language R (R Core Team, 2023), employing `rstanarm` (Goodrich et al., 2023), `marginaleffects` (Arel-Bundock, 2023), and `modelsummary` (Arel-Bundock, 2022) can help predict and further investigate this relationship. The model was fit in a Bayesian framework using `rstanarm` (Goodrich et al., 2023). For the priors, I followed the standard weakly informed prior distributions by using the normal definition with mean 0 and standard deviation 2.5 as used in the `rstanarm` package.

$$
\begin{aligned}
y_i|\pi_i &\sim \text{Bern}(\pi_i) \\
\text{logit}(\pi_i) &= \beta_0 + \alpha^{\text{account}}_{a[i]} + \alpha^{\text{politician}}_{p[i]} + \alpha^{\text{verified}}_{v[i]} \\
\alpha_0 &\sim \text{Normal}(0, 2.5) \\
\alpha^{\text{acc}}_a &\sim \text{Normal}\left(0, \sigma^2_{\text{acc}}\right) \text{ for } a = 1, 2, \ldots, A \\
\alpha^{\text{pol}}_p &\sim \text{Normal}\left(0, \sigma^2_{\text{pol}}\right) \text{ for } p = 1, 2, 3, P \\
\alpha^{\text{ver}}_v &\sim \text{Normal}\left(0, \sigma^2_{\text{ver}}\right) \text{ for } v = 0, 1, V \\
\sigma_{\text{acc}} &\sim \text{Exponential}(1) \\
\sigma_{\text{pol}} &\sim \text{Exponential}(1) \\
\sigma_{\text{ver}} &\sim \text{Exponential}(1)
\end{aligned}
$$

Where y_i is whether a Tweet contained harassment, $\pi_i = \Pr(y_i = 1)$, and α^{account}, $\alpha^{\text{politician}}$, and α^{verified} and are the effect of the type of account a user has, which politician they are replying to, and whether their account is verified. The $a[i]$, $p[i]$, and $v[i]$ refer to which type of account, which politician, and whether a user is verified. A, P, and V are the total number of types of accounts, politicians, and verification options, respectively. The binary response variable, called `harassment_binary`, has a value of 0 if a Tweet does not contain harassment and a value of 1 if it contains harassment. The Positive and Neutral categories on my seven-point scale make up the value of 0 and all remaining categories (Questioning authority through Hate speech) make up the value of 1.

Table 10 presents the estimates generated by the model. For ease of analysis, Table 11 displays the estimates as predictions in a table and Figure 5 shows the predictions graphed.

Table 11 predicts whether a user is likely to send replies that contain harassment as a function of their type of account, whether their account is verified, and which female politician they are replying to. When compared to DPM Freeland, Tweets sent to MP May are an estimated 2% more likely to not contain harassment, while MP Collins is an estimated 6% more likely to receive Tweets that do not contain harassment in comparison to DPM Freeland. For type of account, when personal accounts are compared to professional accounts, professional accounts are an estimated 13% less likely to send Tweets that do not contain harassment. Bots, when

Table 10: Predicting whether a Tweet contains harassment or not, on the basis of the type of account behind the Tweet, which politician the Tweet was in response to, and whether a user is verified.

	(1)
(Intercept)	1.653
Sigma[type_of_account × (Intercept),(Intercept)]	0.397
Sigma[name_of_politician × (Intercept),(Intercept)]	0.216
Sigma[verified × (Intercept),(Intercept)]	0.076
Num.Obs.	4139
R2	0.022
R2 Marg.	0.000
ICC	0.3
Log.Lik.	−1644.171
ELPD	−1652.2
ELPD s.e.	40.1
LOOIC	3304.4
LOOIC s.e.	80.2
WAIC	3304.4
RMSE	0.35

Table 11: Predicting whether a Tweet contains harassment or not, on the basis of the type of account behind the Tweet, which politician the Tweet was in response to, and whether a user is verified.

Term	Contrast	Estimate
name_of_politician	Elizabeth May - Chrystia Freeland	0.02
name_of_politician	Laurel Collins - Chrystia Freeland	0.06
type_of_account	Professional - Personal	-0.13
type_of_account	Bots - Personal	0.08
type_of_account	Spammers - Personal	0.11
type_of_account	Anonymous - Personal	0.12
type_of_account	Suspended/deleted - Personal	0.03
verified	Yes - No	0.02

compared to personal accounts, are an estimated 8% more likely to send Tweets that do not contain harassment, while Spammers are an estimated 11% and Anonymous accounts an an estimated 12% more likely to send Tweets which do not contain harassment. Suspended/deleted accounts are an estimated 3% more likely send Tweets that do not contain harassment in comparison to personal accounts. The model is unable to find a quantitative difference in whether users who are verified or not verified are more likely to send harassing Tweets. The results from the model suggest that despite differences in status and political affiliation across the three politicians, they are almost equally impacted by harassment on Twitter. Moreover, all types of accounts are predisposed to sending harassing Tweets, especially Professional accounts, which I did not hypothesize, but will be explained in my Discussion section.

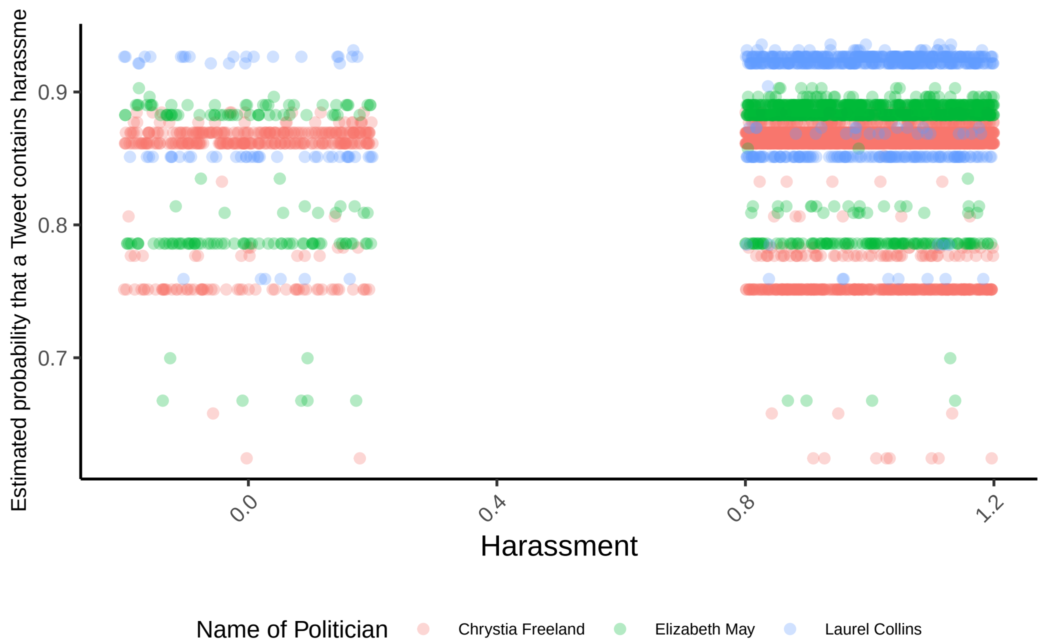

Figure 5: Predicting whether a Tweet contains harassment or not, on the basis of the type of account behind the Tweet, which politician the Tweet was in response to, and whether a user is verified.

7 Discussion

7.1 Severity of Harassment

Based on my hypothesis, I expected that DPM Freeland, followed by MP May, then MP Collins would receive the most severe Tweets, however, MP Collins had more identified instances of Credible threats and Hate speech than MP May (for Hate speech, DPM Freeland had 29 instances, MP Collins had 2, and MP May had 1). I expected that everything of DPM Freeland's would be more severe – with more identified instances of Hate speech and more Credible threats. She still receives considerable amounts of harassment though and being called a "Nazi" constantly was more severe than some of the other names MP May and MP Collins were called. This could be a weakness of my seven-point scale that being called "useless" and a "Nazi" fell under the same category of Name-calling/Gender insults. Qualitative differences such as these could lead me to further refine my quantitative scale.

55% of Tweets fell under the Questioning authority category, which was ultimately higher than hypothesized (see Table 2). As seen in Table 12, Tweets which are categorized as Questioning authority differ from information-seeking questions because users intend to question the abilities of female politicians based on their political affiliation, gender, age, physical appearance, and corresponding assumed qualifications. Although being questioned and tested may not seem like a specifically severe form of harassment, constant microaggressions and undermining comments from the public have been shown to lead female politicians to self-censor and retract from public deliberation, even going as far as deciding not to seek re-election (Harmer & Southern, 2021). Self-censorship and retraction from public life is the opposite of what is needed for gender equality and climate action in politics (Vickery & Everbach, 2018).

Table 12: Sample of a Tweet **Questioning authority** sent to DPM Freeland.

Tweet
@cafreeland @G7 Good topics. Maybe add energy security. And be sure to take notes, because you haven't made progress on any of them. That said, you have made and continue to make, all Canadians poorer.

7.2 Type of Account

For the types of accounts, there were more Spammers and Anonymous accounts than I hypothesized, but these results align with previous research and our understanding of the increasingly toxic nature of Twitter (Phillips, 2015; Theocharis et al., 2020; Wagner, 2020). The high percentage of Anonymous accounts (37%) reinforces McKay & Tenove (2021)'s findings that anonymous (and often harassing) political speech is increasingly common in our contemporary era of deliberative democracy. Given recent changes to Twitter's affordances, Anonymous accounts continue to exist because people are not pleased with the new direction of the platform and do not wish to actively engage, but still wish to have an account.

The high number of Spammers (41%) is consistent with the "Wild West" attitude conceptualized by Megarry (2020). Under previous ownership, many of these accounts would likely be suspended because of enforcement of content moderation rules. The low number of Suspended/deleted accounts was anticipated, because no one is held accountable for their actions anymore. The few deleted accounts were likely people who intentionally wanted to leave the platform. Of those people who are suspended, there are identified instances of temporary suspension (Twitter Developer (2023)) or permanent suspension, which users circumvented by making a new account. Users who made new accounts often indicated this in their bio through phrases like "Back again, hunting libs" or "3rd time? @TXIndep1836 & @TXIndepndnt1836 SILENCED!"

For all three politicians, Positive and Neutral Tweets were most likely to be sent by Personal users, while nearly all other categories of Tweets (Questioning authority through to Hate speech) were most likely to be sent by Anonymous and Spammer accounts. These findings are consistent with the work of McKay & Tenove (2021), Theocharis et al. (2020), and Ward & McLoughlin (2020), who suggest that anonymous and pseudonymous political uses of social media are increasing, but average citizens continue to use social media to weigh in on consequential policy issues and seek information from their federal representatives (instead of engaging through traditional means like email correspondence and town halls).

Although only 1% of accounts were identified as being Professional, who they belong to and their corresponding severity of harassment is notable. Of the replies which were sent by Professional accounts, 64% contained some form of harassment, most often Questioning authority or Name-calling/gender insults. A number of prominent Conservative MPs, including Federal Conservative Leader Pierre Polievre and MPs Stephanie Kusie and Larry Brock responded to Tweets originating on DPM Freeland's account. The estimate the model produced suggesting that Professional accounts are 13% less likely to send a Tweet that does not contain harassment is noteworthy because it illustrates how Conservative politicians are pandering to their base by engaging in aggressive, confrontational behaviour in the House of Commons and mimicking that behaviour online by sending harassing Tweets (Delacourt, 2016). Tweets sent by Conservative MPs were coded as either Questioning authority or Name-calling/Gender insults, which suggests a level of disregard for Parliament as an institution, the authority of female politicians who work on climate and environmental policy, and deliberative democratic speech.

While coding type of accounts, I noticed a number of accounts had at least one red apple emoji and/or sometimes a green apple emoji in their bio or display name. Although there is no academic literature yet to explain this trend, I believe that Conservative supporters added this emoji to their profile as a sign of support for Leader Pierre Polievre, following his October 2023 viral video "chomping down" on an apple while scolding a journalist (Tunney, n.d.). At the time of data collection, 90 unique users added apple emojis to their display name and/or bio, but that number is likely higher with the trend's increasing popularity. Table 13 provides an example. This subtle show of support for the Conservative Party is augmented by direct support for Conservative and right wing political movements in Canada and the United States by the use of words and phrases in user bios such as "#TrudeauMustGo," "#Pierre4PM," "#Trump2024," "MAGA," "CPC," "Conservative," and "PPC". 288 unique users in my dataset explicitly identified themselves as having right-wing and ideological views, which supports my hypothesis.

Table 13: Example of how Twitter users chose to show their support for the Conservative Party and their Leader through the use of the red apple emoji in their display name

Name
Kim -
Erwin Gerrits
Dogwater Dave (Apple Salesman)
sHaDoW - Ralph was The King
Glenda M

7.3 Chrystia Freeland

DPM Freeland's results for severity of harassment and type of account are largely consistent with my expectations and previous research into the harassment faced by eminent female politicians (Rheault et al., 2019). The use of memes, to undermine and harass DPM Freeland prominently features in her sample of Tweets. The term, meme, was first used by evolutionary biologist Richard Dawkins in 1976 and is "… derived from the Greek *mimema*, meaning 'something imitated'; the current usage refers to an idea or bit of content that spreads widely through cyberspace" (Bauman, 2019, pp. 87–88). The memes in DPM Freeland's sample are often unflattering photographs of her, presenting anti-feminist narratives, and intending to undermine her based on her physical appearance (Ging & Siapera, 2019). There was no evidence of deepfakes or highly sophisticated manipulated audiovisual content detected in DPM Freeland's sample (Appel & Prietzel, 2022). Moreover, historical pictures from Nazi Germany in the 1930s/1940s were memed to include the faces of DPM Freeland and sometimes Prime Minister Rt. Hon. Justin Trudeau and NDP Leader Jagmeet Singh, aligning with research conducted by Boudana et al. (2017) which reveals that the revival of historic photographs in the form of memes bolsters public discussion and draws symbolic connections between the past and present. The memes sent in response to Tweets by DPM Freeland are similar to anti-suffragette posters circulating in the early twentieth century which intended to undermine women campaigning for the right to vote and discourage the voices of women in the public sphere (Ging & Siapera, 2019; McKay & Tenove, 2021). Memes and photographs, including the one below, are subjected to Twitter's content moderation rules, as hate speech can be expressed through symbols and images, yet continue to freely circulate on the platform (Carlson, 2021; Twitter Developer, 2023).

Although there were only 29 identified instances of Hate speech in DPM Freeland's sample (see Table 4), qualitative signs of far-right activity and hateful behaviour appeared throughout her sample. Users belonging to fringe minorities will often assign ironic humor and hateful meanings to seemingly normal words and objects, such as the Pepe the Frog character which originated on 4chan, allowing later denial of their political views if questioned (Sarah and Chaim Neuberger Holocaust Education Centre, 2022). A number of users made reference to Pepe in either their username, bio, profile picture, or in their individual replies to Tweets

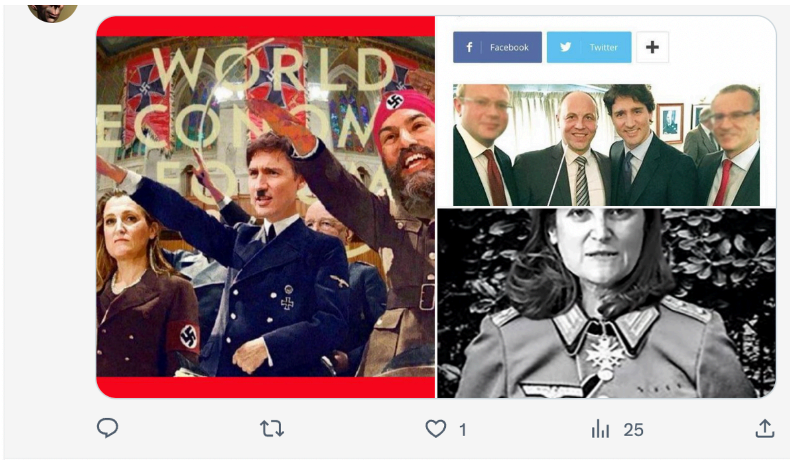

Figure 6: Example of a reply to a Tweet sent by DPM Freeland which revives historical photographs through memes and contains **Hate Speech**

that originated on DPM Freeland's account. Furthermore, at least one user in DPM Freeland's sample also stated their involvement in the far right online men's rights movement called "men going their own way" (MGOW) (Marwick & Caplan, 2018). These preliminary observations of qualitative far right behaviour are concerning for the future of democracy and the active participation of women in politics.

7.4 Elizabeth May

The results for severity of harassment and type of accounts detected in MP May's sample of Tweets are largely consistent with my hypothesis, although there were slightly fewer Positive and Neutral Tweets than anticipated. 55% of Tweets in MP May's sample were coded as Questioning authority, while 28% fall under the Name-calling/Gender insults category (see Table 6). Table 7 emphasizes that combined, Spammers and Anonymous accounts total nearly 80% of all accounts in MP May's networked public – a significant number compared to the 19% of Personal accounts. Given MP May's decades of climate advocacy and personal popularity, a higher number of Personal accounts was anticipated, but the number of Spammers and Anonymous accounts could be explained by the changing platform affordances.

Although memes are not as prominent in MP May's sample of Tweets, user-generated alternative science infographics and links to alternative science YouTube videos and websites repeatedly appeared. Tweets presenting alternative science were often coded as Questioning authority due to the tone and use of demeaning language, as seen in Table 14. Instead of having an entirely civil conversation, MP May's grasp of science and qualifications is challenged.

Table 14: Sample of a Tweet **Questioning authority** sent to MP May.

Tweet
@ElizabethMay Do you remember the acid rain crisis - just about killed us all; then the ozone hole..how we survived? And the ice caps melting..good thing coast didn't get submersed. Now this time can you show legitimate science? No hey? Weird, climatologists have expertise that disagrees

7.5 Laurel Collins

Tweets in MP Collins' sample, for both severity of harassment and type of account were generally more severe than I originally hypothesized. I expected to see a fairly even split between Tweets coded as Questioning authority and Neutral, but ultimately 75% of Tweets were coded as Questioning authority and just 8% as Neutral (see Table 8). Unlike DPM Freeland and MP May, the number of MP Collins Tweets categorized as Name-calling/Gender insults is much lower (at 13%), but there are more Tweets coded as Vicious language, Credible threats, and Hate speech when compared to MP May. For type of account, MP Collins had the highest number of Personal accounts at 27%, the third most chosen category behind Spammers and Anonymous accounts (as shown in Table 9).

Moreover, I identified qualitative differences in the word choice and tone used in replies to MP Collins. Table 15 illustrates the use of patriarchal and paternalistic language directed toward MP Collins, with the use of "my dear". In addition to talking down the qualifications of MP Collins, this user also questions climate science (offering up the popular alternative science suggestion that arson is responsible for forest fires) and voting behaviours in British Columbia. Tweets like this one and others in MP Collins' sample continue to emphasize the microaggressions faced by female politicians as they communicate about consequential policy issues (Harmer & Southern, 2021; Vickery & Everbach, 2018).

Table 15: Sample of a Tweet containing **Name-calling/Gender insults** sent to MP Collins.

Tweet
@Laurel_BC @thenarwhalca Arson my dear. Not climate, CRIMINAL. What the fck is wrong with BC they keep voting NDP. Seriously!?

7.6 Deliberative Democracy

Of the three politicians, MP May's Twitter account best fulfills the definition of deliberative democracy previously outlined, having open conversations with multiple view points and two way flows of communication (despite 55% of her Tweets being coded as Questioning authority).

All viewpoints, including both the fact Canada is not going far enough on climate action and is going too far (especially with carbon pricing) features prominently through the sample of Tweets. Among the users who believe and promote alternative facts, some claim climate change is simply changing weather, or that forest fires are caused by arson, or other niche reasons supported by user-generated websites. Although over 80% of the Tweets in her sample were coded as either Questioning authority or Name-calling/gender insults, people in MP May's networked public more frequently discussed science and policy, albeit sometimes alternative science and facts. MP Collins' networked public also possessed these characteristics, although she was less willing to engage by responding. DPM Freeland received significant amounts of verbal backlash (reinforcing research conducted by Stopfner (2018)) and her staff intentionally did not response to replies from the public, meaning her Twitter account is more a space to broadcast political messages instead of engaging in open and constructive discourse with the public (Marland, 2016; Small, 2016). The lack of two-way discussion, possibly due to DPM Freeland's status and sheer volume of Tweets and replies from the public, is unhealthy for democratic discourse. Although all three politicians could be using their Twitter accounts to more actively engage with the public, the waning engagement is understandable given Twitter's current state. Other more traditional means of two-way dialogue between elected officials and the public, such as town halls and constituent correspondence remain important ways to maintain a deliberative democracy with overwhelming online harassment.

7.7 Limitations

Twitter's ever-changing affordances and focuses as a platform (such as promoting "free speech") directly and indirectly impact the severity of harassment and types of accounts deemed acceptable to keep on the platform. Many of the third-party tools, such as Botometer (Yang et al., 2022), which previously assisted computational social science researchers in determining types of accounts have been rendered unusable with Twitter API changes, limiting my ability to determine which accounts in my study are bots. Consequently, the number of accounts categorized as bots in my study is likely smaller than the actual number of bots. 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 analyzing the data.

Given the in-progress nature of this study, only one coder has coded all the Tweets so far, meaning there is no intercoder reliability. Following the methods outlined by Krippendorff (2013), two additional coders will code a subset of Tweets, before statistically measuring intercoder agreement using `krippendorffsalpha` (Hughes, 2021).

8 Conclusion

In this paper, I examined Tweets explicitly discussing climate change and environmental policy sent to DPM Freeland, MP May, and MP Collins to measure the severity of harassment on a seven-point scale and type of accounts behind the Tweets. My results reveal that over 85% of Tweets sent to the three politicians contained some level of harassment. My model identified and predicted nearly no quantitative differences between Tweets sent to all three female politicians. Spammer and Anonymous accounts were most frequently associated with engaging with the female politicians on Twitter and being responsible for sending the more serve forms of harassment identified. The Tweets analyzed for this study generally matched the criteria of what constitutes healthy democratic discourse, with users with multiple, diverse viewpoints weighing in on the issue of climate change. In future iterations of this study, attention will be turned toward ensuring intercoder reliability, gleaning a better understanding of the frequency of words used in harassing Tweets by doing topic modeling using Latent Dirichlet Allocation, and using LLMs to detect harassment. 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 (Vickery & Everbach, 2018).

Declaration of Conflicting Interests

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Appendix

- My codebook is available here

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