Wartime, Gender, and Social Media: Political Communication before and during the Ukraine War

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Abstract

Politicians use social media to communicate their messages during times of peace and war. While literature tangentially studies the use of social media during conflicts and along gender lines, the two lines of inquiry are rarely explored in tandem. This study uses the Ukraine War as a case study in understanding what women and men politicians say to whom, and how they do it. Variables of gender, time-period, political prominence, social media platform, and party lean are studied using structural topic modelling (STM) and network analysis to understand how war impacts Ukrainian women and men politicians' discussions and interactions on social media. Overall, there were gendered differences in communication content and style by women and men politicians on social media. Women were more collaborative and interactive, seeking support from the West promoting themselves and their countries on social media. Some topics used mostly by men politicians contained military terms and combative verbs. These findings partially support gendered interaction strategies posited in the Women and Peace Hypothesis (Tessler et al., 1999). While Facebook appeared to remain a platform where Ukrainian politicians updated their constituents directly, Twitter saw a massive uptick in English-language tweeting and calls for international support in the war. It is clear, however, that all politicians have taken on a greater purpose of supporting their country through an unprovoked and genocidal war, although they do so in their own ways.

***Note to APSA readers**: Thank you very much for reading this draft of the first study towards my PhD on political communication strategies of, and resulting abuse towards, politicians in Ukraine and Canada. This draft will surely go through multiple re-writes, so constructive feedback at this phase is greatly appreciated.*

Introduction

All but a handful of wars have been fought, communicated, won, and lost, without social media. With it, every word and action of civilians and leaders alike is recorded as it becomes history. Men and women leaders in wartime are expected to approach conflict differently, with men assumed to be inclined towards conflict, and women, compromise (Tessler et al., 1999). In Ukraine, Europe's largest country and largest live conflict since WW2, women are expected to protect their country's family values, culture, language, and spirit, often through subordination in the name of national empowerment (Rubchak, 2001, 2009). But women politicians in wartime have their own story to tell, their own flavours of topics and interactions on social media in attempts protect their country, land, and people. This study is the first of its kind to document and analyse how the Ukraine War impacts women and men politicians' topical and interactive strategies on Facebook and Twitter. Previous studies have analysed gendered interaction strategies during US election campaigns (Meeks, 2016), and how social media was utilized at the start of Ukraine's prolonged war with Russia during the Euromaidan conflicts (Onuch et al., 2021), but this article aims to uncover who says what during times of war, and to whom. Study findings unearth the intersections of gender, social media, political communication, and war.

This article analysed 56,433 Facebook and 22,789 Twitter posts of up to 181 Ukrainian women and men MPs and cabinet ministers who were active on the platforms during pre-wartime and wartime periods. The purpose of this study was to analyse how Ukrainian politicians used social media to spread their messages both before and during Russia's full-scale war in 2022 and whether there were differences along gender lines. STM and network analysis is used to answer a central research question**: How does war impact Ukrainian women and men politicians' discussions and interactions on social media?** The following granular research questions are answered in this article:

- **RQ1**: How do Ukrainian politicians' social media posting behaviour differ according to time-period, gender, social media platform, and language?
- **RQ2a**: To what extent do the themes discussed by politicians fall along traditional expectations of gendered political discourse?
- **RQ2b**: Do topics differ between platforms, politician prominence, time-period, and party lean?
- **RQ3a**: Do women and men politicians exhibit different interaction strategies on Twitter?
- **RQ3b**: Who are the most engaged-with Twitter accounts by women and men politicians during wartime?

It remains unclear why academic intrigue on gendered stereotypes in political discourse has not scaled up for countries outside of the immediate West, and why research on Europe, Eastern Europe, post-Soviet states, has not systematically included Ukraine. Ukraine became an independent nation from the Soviet Union in 1991, and since then its 44-million-person population has progressed on a trajectory towards the ideals of European values and democracy. The entire nation's instant and defiant response to Russia's full-scale war on February 24, 2022, is a testament to Ukraine's national resolve, and value as a country of academic inquiry. Women's empowerment has evolved from the mythology of a true matriarchy to a delusion of equality (Rubchak, 2009, 2011), and modern women are still considered the natural and cultural reproducers of their nation (Kis, 2007). This unique history of feminism, as well as its modern reincarnations in Ukraine, makes the actions and expressions of women politicians an important academic subject.

Literature Review

Gendered stereotypes in politics and leadership

The study of gender in political discourse on social media is a growing field, especially given politicians' increased usage of social media to disseminate their messages. One theory that posits how audiences perceive leaders is Rule Congruity Theory (Eagly & Karau, 2002). Key perceived character traits of women are that they are supportive, giving, and collaborative, while men are aggressive, assertive, and dominant (Meeks, 2012). The latter male traits tend to be perceived as ideal leadership traits, leaving incongruencies between women and positions of power (Eagly & Karau, 2002). Such incongruencies may push women to adopt male traits or continue to emphasize their perceived feminine traits. This may play out on social media, where fewer women participate in online public domains then men (Vochocová et al., 2016). No matter how women portray themselves in politics, they may be negatively stereotyped for being too masculine or too feminine (Carlin & Winfrey, 2009).

In the US context, there are similarities and differences on how women and men use personalization and interactivity on Twitter during election cycles. Gendered communication strategies incorporate a performance of gender as a core component, where women are more conversational and interactive while men communicate more formally and straightforwardly (Meeks, 2016). However, women in the general public have been found to avoid interacting with other Twitter accounts in political discussions (Hu & Kearney, 2021).

In Ukraine, women in the public sphere are often classified as being either too oppressive or oppressed, dictatorial or passive, or domineering or decorative (Rubchak, 2011). Common aspects of life in Ukraine that separate men and women and hold women back from having the best possible wellbeing in Ukrainian society includes occupational segregation, patronizing and sexist language, an overall asymmetry between genders, and a mythological belief that women must maintain the culture and morals of the nation (Kis, 2007; Rubchak, 2009, 2011). This patronizing and sexist language marks a deeper pattern. There is evidence of strong anti-gender campaigns in the neighbouring countries of Poland, Slovakia, and Russia, though Ukraine was not included as a case in the study (Kuhar & Paternotte, 2017). In these neighbouring countries, the environment of anti-gender discourse is embedded in society and government, through opposition of gender-mainstreaming, abortion rights, LGBTQ rights, and through support of 'traditional' family values (where women are expected to be subordinate to men and be primary family carers). Russia actively works to seed anti-gender narratives into their disinformation campaigns both internally and targeting the West, aiming to villainize feminists, the LGBTQ community, and the 'decadent' West in general. Ukrainian women politicians likely operate in similar environments.

Gendered stereotypes during conflicts

Knowledge on gendered stereotypes in political discourse on social media during conflicts is understudied, due to social media mobilization during times of conflict, war, and protest being a relatively recent development (Howard et al., 2011; Onuch et al., 2021; Ronzhyn, 2014). The Women and Peace Hypothesis posits how women and men approach international relations and conflict through their communication styles (Tessler et al., 1999). Women are expected to approach international relations with pacifist views, where they are willing to accept compromise to solve interstate disputes, and do not believe war is as necessary or appropriate as men. This pacifism stems from women's roles as *life-givers* and mothers, who are expected to strive to eliminate violence and find non-violent compromises. While pacifism and tolerance are not necessarily 'female' norms, women's lack of access to legitimate, masculinized power has historically made them seek compromise to obtain at least partial objectives. Men, on the other hand, are expected to approach international relations with the combative view that war is necessary and appropriate in certain situations, and that violence can indeed solve interstate disputes. Men are seen as *life-takers*, who will do so in the name of protecting women and children, as is perceived to be their fatherly responsibility. However, the salience of a conflict makes women *less* likely to call for peace, because the conflict is the central preoccupation of both individuals and states (Tessler et al., 1999).

Structural topic modelling and network analysis to understand social media data

STMs are commonly used to make sense of large amounts of unstructured text, and have previously been used to study crisis communication, though they are most commonly used to analyse non-social media data such as customer reviews (Park et al., 2020). STMs were previously used to decipher clusters of Twitter users after Russia's downing of passenger flight MH17 (Mishler et al., 2015). Clusters found included groups of users who were sympathetic to pro-Ukrainian and pro-Russian viewpoints, and even groups of 'sock puppet' accounts who appeared to be run by the same person, or a small group of people. Network analysis has the power to uncover the patterns of interaction in large amounts of social media posts, and uncover communication strategies of message senders (Jankowicz et al., 2021; Kriel & Pavliuc, 2019).

Methodology

In this study, structural topic modelling and network analysis was used to understand political communication strategies of Ukrainian politicians on Facebook and Twitter during peace and wartime. A topic model collects social media posts as input documents, and studies the co-occurrence of words within the corpus of documents to uncover patterns (M. Roberts et al., 2013; M. E. Roberts et al., n.d.). STMs are an extension of the Latent Dirichlet Allocation topic model as they incorporate metadata about the documents into the model and establish the effect sizes of metadata on topics (Blei, 2003). Metadata considered in this study were: gender of Ukrainian politicians, whether the social media posts were created before or during Russia's full-scale war, the platform the document was posted to, the prominence of politicians, and the lean of the politicians' parties. Politician-level information was first collected in a database before social media data collection and analysis was conducted.

Data Collection

The first step in creating a database of Ukrainian politicians was to create a spreadsheet containing the names and political parties of Ukrainian MPs and cabinet ministers. This information was collected from the Wikipedia page for the Ukrainian Verkhovna Rada (Parliament) ("List of Members of the Parliament of Ukraine, 2019–2023," 2022). The gender of politicians was not provided but was assumed based on the first names of the politicians. Any names that were not easy to guess the gender of were checked by searching the politician's name on Google and assuming their gender based on their image and further context. This process meant that gender identities of all politicians had to be externally assumed, but in the absence of an official 'gender' column this was the only possible option. An evaluation on assumed genders was conducted while compiling user IDs for politicians on Facebook and Twitter manually. As each politician's user ID was added to the database, a manual check that the gender identity they present in their profile photo matches the gender marking in the 'gender' column of the database.

To collect Facebook posts from the Ukrainian politicians, they were searched and added to a CrowdTangle 'list', which allows for groups of Facebook pages to be categorized and analysed in-house, or for their information to be downloaded locally for further analysis (2022a). Each politician's name was searched in both Latin and Cyrillic characters using the 'Add Page' function and their user ID added to the database when the individual was found. Searching for their names in Cyrillic was valuable because 36% of Ukrainian politicians had their names listed in Cyrillic on Facebook, and because Cyrillic names can have multiple variations when translated to Latin characters (i.e., Леся can be translated to Lesia, Lesya, or Lesiya). After this detailed and manual search process, 198 out of 423 profiles were located and added to the list. Crowdtangle only allows 'public' individuals (pages or profiles with over 5,000 followers) to be added to lists, so some politicians' profiles or pages could not be added or analysed in this study. After the list of 198 politicians was created, the 'Get History' function in Crowdtangle was used to download each politician's entire post history in CSV format. This gathered a total of 191,288 Facebook posts from the 198 politicians. The final two datasets for this analysis (non-wartime: February 23 – June 28, 2021, wartime: February 23 – June 28, 2022), after deleting blank posts, gathered 17,815 and 38,628 posts, respectively.

For Twitter collection, a similar process was followed where each politician's name in Latin and Cyrillic characters was searched in Twitter's list function (Pavliuc, 2022). This process gathered 122 profiles, with no minimum follower amount. After finalizing this list, the list of these profiles was exported, and used to collect all tweets through the Tweepy Twitter-collection package in Python. Twitter only allows the most recent 3,200 tweets to be scraped from users in its open API. Scraping the 121 profiles for their 3,200 most recent tweets gathered 99,894 tweets. Only 13 profiles gathered around 3,200 tweets, meaning that their oldest tweets were likely not captured using this collection method. Though, all 13 profiles had full datasets in the pre-wartime (February 23 – June 28, 2021) period, meaning that full samples were gathered for all profiles in the time-periods analysed in this study. The final two datasets for this analysis (non-wartime: February 23 – June 28, 2021, wartime: February 23 – June 28, 2022), after deleting blank posts, gathered 3,022 and 19,767 posts, respectively.

Metadata for Structural Topic Models

Gender, time-period, and social media platform, prominence, and party lean are the metadata analysed in this study. Gender, time-period, and platform were analysed in RQ1. All variables were analysed in the STMs in RQ2a and RQ2b. Gender and prominence on Twitter were analysed in the network analysis in RQ3a and RQ3b.

Gender (women, men)

Gender of Ukrainian politicians is the main variable compared against others in this study. The purpose of this study is to add the case of Ukraine to theories of gendered political communication, in addition to theories of women leaders during times of war. A scan of government databases and news articles found that no current Ukrainian politicians identify as non-binary.

Time-period (non-wartime, wartime)

The wartime period analysed in this study ran from February 23, 2022 (the day before Russia launched their full-scale war on Ukraine) to June 28, 2022 (the final possible date of data collection for this study). This four-month, 126-day period captures the entire first 'shock' of the war, and the period where politicians would have transitioned and likely settled into new political communication strategies on their social media profiles. For the non-wartime period, February 23 – June 28, 2021, was selected. Choosing the same calendar dates but in a different year ensured that there would not be any differences in seasonality. This time-period in 2019 or 2020 was not selected because the previous Ukrainian presidential elections were held on March 31 and April 21, 2019, and the Covid-19 period in early-2020 likely impacted politicians' social media usage patterns. The gradual build-up of Russian troops on Ukraine's border began in late-March 2021 but did not become a prominent news headline until months later when they started to reach critical masses of troops. Though, given Russia's annexation of Crimea in 2014, Ukraine has perpetually been situated in a state between war and peace since then. It is assumed that February 23 – June 28, 2021 (also 126 days), captures as typical of a time-period as possible.

Platform (Twitter, Facebook)

Twitter and Facebook were selected due to their differing target audiences and relative ease of data collection. Facebook was commonly used among Ukrainians during the 2013-2014 Euromaidan protests to receive updates from protest leaders and political figures, and to organize collective actions (Onuch et al., 2021; Ronzhyn, 2014). In Western Ukraine, Facebook use is concentrated in urban areas (Puhach & Mezentsev, 2021). Twitter was also selected for analysis because it is commonly used among Western intellectuals, journalists, and politicians, and given Ukraine's need for Western military and financial support during the war, studying how Ukrainian politicians utilize Twitter between the non-wartime and wartime periods is of interest. During the Euromaidan protests, Twitter was found to be used to reach foreign audiences and provide brief tactical updates to protestors, such as on police whereabouts (Ronzhyn, 2014). Due to differing usage patterns on Facebook and Twitter during Euromaidan, it is important to understand how these two platforms are utilized during wartime, and by whom. Telegram was also considered as a data source, but the search function on Telegram proved to be highly rigid and was therefore less reliable to find politicians' pages when their names were searched in Latin and Cyrillic characters.

Politician Prominence (prominent, not prominent)

Politicians considered prominent included political party leaders, current and former presidents, and cabinet ministers. This criterion labelled 52 politicians as prominent. 24 prominent politicians had Facebook accounts, and 19 had Twitter accounts which could be analysed in this study.

Party Lean (Opposition – For Life Party, not Opposition – For Life Party)

To capture ideological differences in Ukrainian politics and pro-Russian and pro-European lines, a binary variable for party lean was created and used in the STM. The only party categorized as pro-Russian was 'Opposition – For Life', a political party that was banned at the start of the full-scale war for having links to the Kremlin (2022b). All other political parties were separately categorized as 'not Opposition – For Life'. Of the 45 politicians who are members of the party, eight had Facebook accounts and 10 had Twitter accounts which could be analysed in this study. Future iterations of this research may involve categorizing Ukraine's political parties further according to how nationalistic they are, to assess whether nationalism overpowers gender norms during times of war.

Data Analysis

RQ1: How do Ukrainian politicians' social media posting behaviour differ according to time-period, gender, social media platform, and language?

Answering this RQ required the compilation of descriptive statistics about gender, platform, and language use before and during wartime. After the Facebook and Twitter data were collected, it was imported into a Python Jupyter notebook. Posts falling within the non-wartime and wartime periods were categorized as such. The gender of each politician was merged with each social media post to calculate how many posts were published to each platform by women and men, as well as the total number of women and men posting to each platform. The Google Translator package was used to add a new column of language to each Facebook and Twitter post. A manual evaluation of a random sample found the translations to appear accurate by a fluent Ukrainian and English language speaker. The English-translated social media posts were used throughout this study and fed into the STM. All descriptive statistics for RQ1 are summarized in Table 1.

RQ2a: To what extent do the themes discussed by politicians fall along traditional expectations of gendered political discourse?

To answer RQ2, information about prominence and party lean in the Ukrainian politician database were merged with the collected Facebook and Twitter data. The 'documents' (Facebook and Twitter posts) for the STM were then cleaned: the text was converted to lowercase, and all hyperlinks, symbols, and extra spaces were removed. The Facebook and Twitter data were processed separately until they were merged, and the following columns were saved in the final CSV containing the documents and metadata for the STM:

- *Document columns:*
    - Index (Integer)
    - Document (String, of each social media post)
- *Metadata columns*:
    - Time-period (Binary, 'Non-war' or 'War')
    - Gender (Binary, 'Woman' or 'Man')
    - Prominence (Binary, '0' = not prominent or '1' = prominent)
    - Platform (Binary, 'Facebook' or 'Twitter')
    - Party Lean (Binary, 'Opposition – For Life' or 'Not Opposition – For Life')

To run the STM, the 'STM' package in R was used, and accessed through a Jupyter notebook. R code from STM tutorials and the official STM documentation were compiled according to the needs of this study (Bail, n.d.; Caberlin, 2019; Monroe, n.d.; M. E. Roberts et al., n.d.). The Document column was processed through the textProcessor function which creates a corpus, converts the text to lowercase, stems the words, and removes punctuation, stopwords, and numbers from the documents. The corpus was then run through the prepDocuments function which removes highly frequent terms from the corpus and deletes documents with no words.

Once the documents were prepared six topic models were then run on the data, searching for 30, 40, 50, 60, 70, and 80 topics. Each model incorporated the prevalence of all metadata (gender, time-period, prominence, platform, and party lean), and used the 'spectral' initiation type. After all models were run, they were visually compared for differences in two common metrics of topic quality: exclusivity (how unique words are to a given topic) and semantic coherence (how often words that are probable to co-occur appear in the same document) in Figure 1 (Caberlin, 2020).

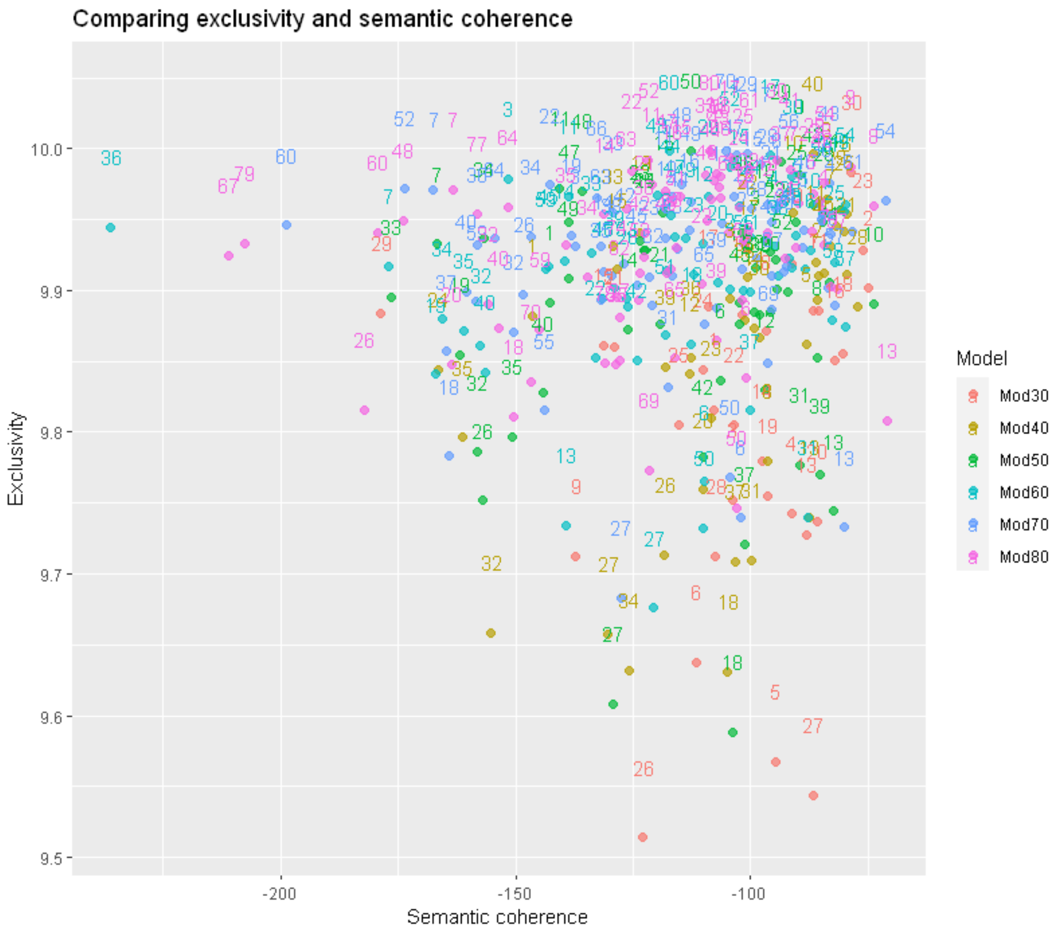

Figure 1: Comparison of exclusivity and semantic coherence in models with 30, 40, 50, 60, 70, and 80 topics.

The models containing 30, 40, and 50 topics appeared to contain several outlying topics with low exclusivity, meaning that 30-50 topics was not enough to capture the range of topics discussed in the data. The models containing 60 and 80 topics contained some topics with low semantic coherence, meaning that words that were calculated as probable to co-occur in given documents did not. Due to these shortfalls, the model with 70 topics was chosen for onward analysis in this study.

After selecting the 70-topic STM for further analysis, the top words per topic and effects of metadata on each topic were exported for further analysis. To finalize the topics, a manual process of selecting two to five top words which capture the essence of each topic was conducted, as well as creating a new topic variable which captured larger groupings of topics. These larger topic groupings included, for example, ‘call for support’, ‘military’, ‘people affected by war’, and ‘Ukrainian culture’ and are paired with their top words in Table 2. The top words per topic are used to answer RQ2a, but onwards only the larger topic groupings are used as topics to simplify the analysis. Effects of each type of metadata were also exported and ordered by their T-values (which determine the strength and direction of the effect) as can be seen in Table 2.

To answer RQ2a, the topics were summarized by whether they were more likely to be used by women (if the effects were significant and the T-value was negative), men (if the effects were significant and the T-value was positive), or by both genders (if there was no significant effect of gender on the topic). The patterns in gendered topic usage are discussed in the Results section for RQ2a, based on Table 3.

RQ2b: Do topics differ between platforms, politician prominence, time-period, and party lean?

To answer RQ2b, the same process was used to the analysis of gender in RQ2a but was applied to other metadata (platform, prominence, time-period, and party lean). The patterns which can be observed in Tables 4 and 5 are discussed in the Results section for RQ2b.

RQ3a: Do women and men politicians exhibit different interaction strategies on Twitter?

Answering RQ3a required accessing the pre-processed Twitter data and extracting all instances where a politician mentioned another Twitter user with the '@' symbol. After each mention was extracted and added to a new row (as a Target node) alongside the politician who sent the tweet (the Source node), the gender, time-period and prominence of each Source politician was merged with the table. The party lean of politicians was not included in this analysis because only three Opposition – For Life politicians used the '@' interaction affordance of Twitter in the dataset.

The final dataset which contained the following columns was then uploaded into Gephi, a network analysis and visualization software (Bastian et al., 2009):

- *Interaction data:*
    - Source (username of Ukrainian politician who sent the tweet)
    - Target (username of Twitter account mentioned by the Source)
- *Metadata:*
    - Gender of Source politician (Binary, 'Woman' or 'Man')
    - Prominence of Source politician (Binary, '0' = not prominent or '1' = prominent)
    - Time-period (Binary: 'non-wartime' or 'wartime)

In Gephi, the weighted network was visualized using the Force Atlas 2 algorithm and was coloured by politician gender in Figure 2. The following network statistics for each node (both Source and Target) were calculated (definitions from (Grandjean, 2015)):

- In-degree (number of links sent towards a node)
- Out-degree (number of links sent by a node)
- Degree (sum of a node's in- and out-degree)
- Component number (proximity of a node to highly connected network regions)
- Eigen centrality (Influence of a node relative to its neighbours)
- Eccentricity (Maximum graph distance between a node and all other nodes)
- Closeness centrality (Closeness of a node to the entire network)
- Betweenness centrality (Importance of a node in bridging multiple highly connected network regions)
- Modularity class (centrality of a node within network communities)

The network statistics of Ukrainian politicians were then averaged by gender and prominence, displayed in Table 6, and patterns were discussed in the Results section of RQ3a.

RQ3b: Who are the most engaged-with Twitter accounts by women and men politicians during wartime?

To answer RQ3b, the in-degrees of all nodes (either Source politicians or Target Twitter users) were calculated, and the top 25 mentioned Twitter accounts in the dataset are displayed in Table 7 and discussed in the Results section for RQ3b.

Results

RQ1: How do Ukrainian politicians' social media posting behaviour differ according to time-period, gender, social media platform, and language?

There is limited literature on how a country becoming a victim of war impacts its politicians' social media posting habits along platform, gender, and lingual lines. Table 1 captures the key descriptive statistics required to answer RQ1.

Facebook (n=56,443)					
Non-wartime (n=17,815, 32%)			**Wartime (n=38,628, 68%)**		
Num. posts	Women Men	5,481 (31%) 12,334 (69%)	**Num. posts**	Women Men	11,274 (29%) 27,354 (71%)
Num. politicians posting	Women Men	46 (27%) 126 (73%)	**Num. politicians posting**	Women Men	50 (28%) 131 (72%)
Num. posts per language	Ukrainian Russian English Other	13,951 (78%) 1,700 (10%) 62 (0.4%) 2,102 (11.6%)	**Num. posts per language**	Ukrainian Russian English Other	27,841 (72%) 4,321 (11%) 991 (3%) 5,475 (14%)
Twitter (n=22,789)					
Non-wartime (n=3,022, 13%)			**Wartime (n=19,767, 87%)**		
Num. posts	Women Men	509 (17%) 2,513 (83%)	**Num. posts**	Women Men	9,832 (49%) 9,937 (51%)
Num. politicians posting	Women Men	10 (24%) 31 (76%)	**Num. politicians posting**	Women Men	25 (49%) 51 (51%)
Num. posts per language	Ukrainian English Russian Other	2,000 (66%) 636 (21%) 242 (8%) 144 (5%)	**Num. posts per language**	English Ukrainian Russian Other	15,620 (79%) 2,750 (14%) 255 (1%) 1,142 (6%)

Table 1: Descriptive statistics on Facebook and Twitter data collected for this study.

Overall, activity on Facebook according to gender and language appeared to remain proportionately stable between the non-wartime and wartime periods. While the number of posts doubled between the periods, the proportion of Facebook posts by women and men politicians, the number of women and men politicians posting, and the languages they posted in remained about the same.

Twitter appears to be the platform where posting behaviour changed the most between the non-wartime and wartime periods. There was a six-fold increase in posting Twitter after the wartime period started, with women politicians increasing the number of tweets they put out from 17% of non-wartime tweets to 49% of all wartime tweets. The number of women posting to Twitter also increased from 24% during the non-wartime period to 49% during wartime.

The starkest difference in behaviour was the jump in English-language tweeting. In the non-wartime period, 21% of tweets were in English while in the wartime period, 79% were in English. Ukrainian language tweeting also decreased from 66% during the non-wartime period to 14% during the wartime period.

RQ2a: To what extent do the themes discussed by politicians fall along traditional expectations of gendered political discourse?

The Women and Peace Hypothesis assumes that women approach conflict with pacifist views in search of compromise, while men are competitive, combative, and violent (Tessler et al., 1999). Tables 2 and 3 show the differences in topic use among women and men, including between topics pertaining to combat (war) from a tactical and optimistic perspective, calls for support, and discussion of people effected by the war. Symbols for hashtag use (#) and Twitter user mentions (@) are also included in Table 2 if the top topics included words that appeared to be hashtags (i.e., 'standwithukraine') or mentions (i.e., borisjohnson).

Topics used by Women & Men (order = T value, n = 70)							
Gender of Topic	**Topic**	**Top Words**	**Estimate**	**Std. Error**	**T value**	**Pr(>|t|)**	**Sig.**
Women	Call for support (#, @)	no fly zone, help, UK leaders	-2.33E-02	5.84E-04	-39.847	< 2e-16	***
Women	People affected by war	children, women, die, mother	-0.00748	0.000528	-14.153	< 2e-16	***
Women	NA	know, look, like	-0.00517	0.000379	-13.65	< 2e-16	***
Women	People affected by war	Mariupol, civilian, humanitarian, evacuate	-0.00626	0.000552	-11.341	< 2e-16	***
Women	Gov't affairs/infrastructure	crime, prosecutor, evidence	-0.00638	0.000565	-11.302	< 2e-16	***
Women	Gov't affairs/infrastructure	Moscow, church, orthodox	-0.0055	0.000515	-10.696	< 2e-16	***
Women	Call for support (#, @)	NATO, closethesky, EU leaders	-0.00584	0.000563	-10.378	< 2e-16	***
Women	People affected by war	stay home, shelter	-0.00286	0.000305	-9.372	< 2e-16	***
Women	Youth	children, school	-0.00467	0.000507	-9.209	< 2e-16	***
Women	Social/TV Media	espresso, talk, broadcast	-0.00483	0.000537	-8.997	< 2e-16	***
Women	Global impact of war	Chernobyl, nuclear, threat, Enerhodar	-0.00414	0.000484	-8.547	< 2e-16	***
Women	Gov't affairs/infrastructure	parliament, council, Strasbourg	-0.00302	0.000358	-8.433	< 2e-16	***
Women	Gov't affairs/infrastructure	nurse, cancer, medic, save	-0.00455	0.000548	-8.307	< 2e-16	***
Women	Gov't affairs/infrastructure (@)	UA Holos party politicians	-0.002	0.000285	-7.037	1.98E-12	***
Women	Social/TV Media	Telegram, Whatsapp, Instagram	-0.00219	0.000398	-5.502	3.76E-08	***
Women	Gov't affairs/infrastructure	Covid vaccine, health	-0.00228	0.000443	-5.139	2.78E-07	***
Women	Russia aggressor (#)	StopPutin, destroy, kill, BuchaMassacre	-0.00272	0.000715	-3.805	0.000142	***
Women	Gov't affairs/infrastructure	tax, pensions, budget	-0.0013	0.000492	-2.65	0.00805	**
Women	War - optimism (@)	EU membership, union, status	-0.00133	0.000659	-2.024	0.042974	*

Women	Ukrainian culture	Easter, holiday, Happy, vyshyvanka	-0.00158	0.000877	-1.802	0.071471	.
Women	War - optimism	community, district, repair, territory	-0.00094	0.000528	-1.786	0.07416	.
Both	Gov't affairs/infrastructure	oligarch, asset, fund	-5.26E-04	3.85E-04	-1.366	0.171952	
Both	Gov't affairs/infrastructure	corruption, reform	-0.00043	0.000318	-1.348	0.177544	
Both	Military	martial law, military	-0.0008	0.000628	-1.278	0.20121	
Both	Gov't affairs/infrastructure	transport, car, rail	-0.00027	0.00035	-0.764	0.4451	
Both	Ukrainian culture	Kobzar, literature, Shevchenko	-0.00028	0.000373	-0.746	0.456	
Both	Ukrainian culture	culture, history, nation	-0.00017	0.000425	-0.405	0.685547	
Both	Gov't affairs/infrastructure	forest, zoo, environment, nature	-4.89E-05	3.79E-04	-0.129	0.8974	
Both	NA	time, year, ago	2.14E-05	1.95E-04	0.109	0.9129	
Both	Gov't affairs/infrastructure	loans, mortgages, agreements	3.27E-05	2.70E-04	0.121	0.903719	
Both	Call for support	humanitarian aid, bulletproof, thank	0.000146	0.000722	0.203	0.83938	
Both	NA	today, another, yesterday	1.89E-05	3.55E-05	0.531	0.595166	
Both	Sanctions	SWIFT, IBAN, bank	0.000151	0.000235	0.644	0.519559	
Both	Ukrainian culture	Ukraine, language, resist	9.64E-05	1.05E-04	0.918	0.35883	
Both	People affected by war	Kyiv, curfew	0.000296	0.000292	1.016	0.30971	
Both	Ukrainian culture	Eurovision, Kalush	0.000462	0.000452	1.022	0.306561	
Both	Gov't affairs/infrastructure	Diya app, service, convenience	0.000674	0.000535	1.26	0.207798	
Men	Gov't affairs/infrastructure (@)	Ukraine, ministry, EU/US/CA Leaders	0.000778	0.000455	1.71	0.08722	.
Men	Gov't affairs/infrastructure	understand, country, fact, politician	0.000791	0.000409	1.933	0.05324	.
Men	Russia aggressor (#)	report, Kremlebot, journalist	0.000593	0.000294	2.015	0.0439	*
Men	Gov't affairs/infrastructure	verkhovna rada, law	0.001183	0.000571	2.073	0.03822	*
Men	People affected by war	necessity, work, wartime	3.79E-04	1.43E-04	2.646	0.008144	**
Men	Sanctions (@)	sanctions, boycott, Russian companies	0.001561	0.000574	2.721	0.00651	**
Men	Gov't affairs/infrastructure	develop industry, economy	0.001175	0.000428	2.747	0.006009	**
Men	Russia aggressor (#)	world, war, Putin, evil, FightLikeUkrainian	0.001092	0.000378	2.889	0.003869	**
Men	Sanctions	sanction, Russian oil	0.001532	0.000494	3.099	0.001942	**
Men	War	Belarus, Minsk, Lukashenko, border	0.001584	0.000369	4.289	1.79E-05	***
Men	Gov't affairs/infrastructure	servant, people, deputy	0.00147	0.000338	4.352	1.35E-05	***
Men	Youth	youth, sport, Ukraine	0.002634	0.000589	4.472	7.78E-06	***
Men	NA	urgent, sign, fuck, wait	0.000722	0.000155	4.671	3.00E-06	***
Men	Accuse pro-Russian politicians	Yanukovych, Medvedchuk, Sharia, treason	0.002246	0.000476	4.715	2.42E-06	***
Men	Global impact of war	grain exports, Black Sea	0.002467	0.000475	5.195	2.05E-07	***
Men	People affected by war	occupy, Crimea, Donbas,	0.002753	0.000506	5.446	5.17E-08	***

		deport					
Men	Global impact of war	gas, energy, price, supply	0.002335	0.000386	6.054	1.42E-09	***
Men	Military	tank, aircraft, missile	0.004568	0.000699	6.532	6.54E-11	***
Men	Gov't affairs/infrastructure	cabinet, state, ministry	0.002358	0.00036	6.558	5.47E-11	***
Men	Gov't affairs/infrastructure	UA city names (Kharkiv, Cherkask, Donetsk)	0.003926	0.000504	7.785	7.04E-15	***
Men	War - optimism	victory, soon, definite	0.002632	0.000294	8.939	< 2e-16	***
Men	Social/TV Media	video, news, platform	0.001957	0.000215	9.097	< 2e-16	***
Men	Sanctions (@)	block Google, Microsoft, Meta, Netflix	0.003898	0.000397	9.827	< 2e-16	***
Men	Russia aggressor	Russia, aggressor, invasion, Ukraine	0.004246	0.000402	10.55	< 2e-16	***
Men	Gov't affairs/infrastructure	southern cities, Odesa, Mykolaiv	1.90E-03	1.75E-04	10.875	< 2e-16	***
Men	Russia aggressor	burn, crook, rashist	2.46E-03	2.22E-04	11.046	< 2e-16	***
Men	Call for support (#, @)	support, Ukraine, Poland, International leaders	0.005593	0.000506	11.062	< 2e-16	***
Men	Gov't affairs/infrastructure	economy, natural resources	0.003965	0.000326	12.166	< 2e-16	***
Men	Russia aggressor	Kremlin, lie, Nazi, propaganda	0.005204	0.000418	12.454	< 2e-16	***
Men	War (@)	Ukraine, meet, discuss, security, US leaders	0.007414	0.000591	12.545	< 2e-16	***
Men	Military	courage, defend, fight	8.52E-03	6.41E-04	13.294	< 2e-16	***
Men	Gov't affairs/infrastructure	trade union, worker	0.005237	0.000339	15.469	< 2e-16	***
Men	Military	command, armed, forces	9.62E-03	5.94E-04	16.178	< 2e-16	***

Table 2: Highly significant topics used by Women, men, and both genders on Facebook and Twitter.

Distribution of Topics used by Women, Both, Men (Interactions omitted)			
Topic	Women (n=21)	Both (n=16)	Men (n=33)
Gov't affairs/infrastructure	33% (7)	46% (6)	30% (10)
People affected by war	14% (3)	8% (1)	6% (2)
Call for support	9% (2)	8% (1)	3% (1)
War - optimism	9% (2)	0	3% (1)
Social/TV Media	9% (2)	0	3% (1)
Russia aggressor	5% (1)	0	15% (5)
Global impact of war	5% (1)	0	6% (2)
N/A	5% (1)	15% (2)	3% (1)
Youth	5% (1)	0	3% (1)
Ukrainian culture	5% (1)	31% (4)	0
Military	0	8% (1)	9% (3)
Sanctions	0	8% (1)	9% (3)
War	0	0	6% (2)
Accuse pro-Russian politicians	0	0	3% (1)

Table 3: Distribution of topics used mainly by women and men, and both genders. To capture topic distribution within groups, the percentage of topic use over total topics within each group is provided, alongside the absolute value.

Table 3 displays a summary of significant and insignificant topics used by women and men in Table 2. The 'Both' column captures topics whose usage was not significantly more likely to occur with women or men. The summary in Table 3 shows that women and men often discussed topics regarding government affairs and infrastructure, with six topics spanning use by both genders. Such topics used by both genders included discussing Ukraine's Diya app (which allows citizens to access digitized government services), corruption reform, loans and mortgages, and the environment. Women most significantly discussed crime, prosecutions, and the Russian orthodox church, while men discussed trade unions, the economy, and natural resources. Only three out of 23 government affairs/infrastructure topics were significantly likely to be discussed during wartime, meaning that most of these topics were likely discussed before the war.

Topics most highly discussed by women were calls for support, optimism about winning the war, and mentions of social and television media. Women's calls for support included pleading to UK and EU leaders (by mentioning several Twitter usernames of leaders) and NATO to implement a 'no fly zone', including with the hashtag #CloseTheSky. This call was made early in the war by Ukrainian politicians and civilians alike for NATO to prohibit Russian aircraft from entering parts of Ukrainian airspace after a maternity hospital was bombed in Eastern Ukraine (Demianyk, 2022). Women also expressed optimistic views about the war by discussing Ukraine's granting of EU candidate status and discussing how communities will repair their territory. Mentions of social and television media appeared to be encouraging their audiences to follow them on social media and watch their television interviews.

Topics most highly discussed by men regarded calling Russia the aggressor, discussing the military, and sanctions. In discussion about Russia as the aggressor, men discussed Kremlin lies and Nazi propaganda, used the terms 'crook' and 'rashist' (a new term to describe Russian fascism under Vladimir Putin's rule (Mirovalev, 2022)), and bluntly called Russia the aggressor, and Putin evil. One topic encouraged bravery using the #FightLikeUkrainian hashtag alongside the latter 'Putin' and 'evil' terms. Military topics mainly included discussion of the Ukrainian Armed Forces, tanks, missiles, and aircraft, and the verbs 'fight', 'defend', and the word 'courage'. Men's discussion of sanctions included calling for a 'block' of popular Western internet platforms (including Google, Microsoft, Meta, and Netflix) and sanctions on Russian oil and companies.

One group of topics used by both men and women were about Ukrainian culture. The four Ukrainian culture topics that were not significantly more likely to be used by either women or men discussed Ukrainian literature, history, language, and Ukrainian band Kalush Orchestra's win at Eurovision 2022. Only one Ukrainian culture topic was slightly more likely to be used by women than men, and it discussed Easter holidays and vyshyvanky (Ukrainian traditional embroidered shirts).

Although RQ3 addresses interaction strategies of politicians, the topic column in Table 2 captures whether names of international world leaders or hashtags were used.

RQ2b: Do topics differ between platforms, politician prominence, time-period, and party lean?

Due to a STM's ability to discern topics given certain metadata, it is also possible to calculate which topics are more likely to occur along platform, time-period, politician-prominence, and party lines.

Topic	Distribution of Topics used on Facebook, both, or Twitter			Distribution of Topics used non-wartime, both, or during wartime		
	Facebook (n=45)	Both (n=3)	Twitter (n=22)	Non-wartime (n=31)	Both (n=13)	Wartime (n=26)
Gov't affairs/infrastructure	40% (18)	66% (2)	14% (3)	45% (14)	46% (6)	12% (3)
N/A	9% (4)	0	0	3% (1)	8% (1)	8% (2)
Military	9% (4)	0	0	0	8% (1)	11% (3)
Ukrainian culture	7% (3)	33% (1)	4% (1)	13% (4)	0	4% (1)
People affected by war	7% (3)	0	14% (3)	10% (3)	8% (1)	8% (2)
Sanctions	7% (3)	0	4% (1)	0	8% (1)	11% (3)
War - optimism	4% (2)	0	4% (1)	6% (2)	0	4% (1)
Youth	4% (2)	0	0	6% (2)	0	0
Social/TV Media	4% (2)	0	4% (1)	3% (1)	0	8% (2)
Russia aggressor	4% (2)	0	18% (4)	0	8% (1)	19% (5)
Global impact of war	2% (1)	0	9% (2)	6% (2)	8% (1)	0
Call for support	2% (1)	0	14% (3)	0	8% (1)	11% (3)
War	0	0	9% (2)	3% (1)	0	4% (1)
Accuse pro-Russian politicians	0	0	4% (1)	3% (1)	0	0

Table 4: Distribution of topics used between Twitter and Facebook, and during non-wartime and wartime periods. To capture topic distribution within groups, the percentage of topic use over total topics within each group is provided, alongside the absolute value.

Topic	Distribution of Topics used by not Prominent, both, or Prominent politicians			Distribution of Topics used by not Opposition For Life, both, or Opposition For Life politicians		
	Not Prominent (n=38)	Both (n=6)	Prominent (n=26)	Not Opposition For Life (n=30)	Both (n=26)	Opposition For Life (n=14)
Gov't affairs/infrastructure	34% (13)	50% (3)	27% (7)	43% (13)	19% (5)	36% (5)
People affected by war	10% (4)	0	8% (2)	3% (1)	8% (2)	21% (3)
Military	8% (3)	0	4% (1)	13% (4)	0	0
Ukrainian culture	8% (3)	0	8% (2)	10% (3)	4% (1)	7% (1)
Russia aggressor	8% (3)	16% (1)	8% (2)	3% (1)	19% (5)	0
Youth	5% (2)	0	0	7% (2)	0	0
Social/TV Media	5% (2)	0	4% (1)	3% (1)	4% (1)	7% (1)
N/A	5% (2)	0	8% (2)	3% (1)	8% (2)	7% (1)
Call for support	5% (2)	16% (1)	4% (1)	0	12% (3)	7% (1)
War - optimism	3% (1)	0	8% (2)	7% (2)	0	7% (1)
War	3% (1)	0	4% (1)	3% (1)	4% (1)	0
Global impact of war	3% (1)	0	8% (2)	0	12% (3)	0
Accuse pro-Russian politicians	3% (1)	0	0	0	0	7% (1)
Sanctions	0	16% (1)	11% (3)	3% (1)	12% (3)	0

Table 5: Distribution of topics used between Twitter and Facebook, and during non-wartime and wartime periods. To capture topic distribution within groups, the percentage of topic use over total topics within each group is provided, alongside the absolute value.

Tables 4 and 5 show that government affairs and infrastructure topics were more likely to be discussed on Facebook during non-wartime, and by non-Opposition For Life and non-prominent politicians. This is not surprising given that Facebook appears to be the platform where politicians communicated in Ukrainian (presumably with constituents) roughly equally during the non-wartime and wartime periods (as seen in Results: RQ1).

The military was more likely to be discussed on Facebook during wartime, by both prominent and non-prominent politicians, albeit in different ways. Ukrainian culture topics were discussed across social media platforms, mainly before the war, and by both prominent, non-prominent, pro-European and pro-Russian politicians.

Topics regarding people effected by the war, optimism about the war, and the war in general (without overt optimism) were discussed both in the non-wartime and wartime time-periods. This is likely due to the existing Russian annexation of Crimea and parts of Eastern Ukraine before the full-scale invasion began in 2022 (the wartime period in this study). This persistence of some form of war since 2014 may explain the blurred lines between non-wartime and wartime topics.

Twitter appeared to be a platform where it was more likely for politicians to discuss topics regarding Russia as an aggressor, calls for support from the West, as well as discussing people affected by the war (the latter also appeared on Facebook). Given the finding that English-language usage shot up during the wartime period on Twitter (see results: RQ1) these findings are not surprising.

RQ3a: Do women and men politicians exhibit different interaction strategies on Twitter?

93% of Twitter interactions occurred during the wartime period, meaning that politicians increased their use of mentioning other Twitter users by 13 between the non-wartime and wartime periods.

Despite fewer women politicians using Twitter during both non-wartime and wartime periods and tweeting less than men during both time-periods, women politicians had a higher average out-degree than men, meaning that, on average, women used the @ function to mention and interact with people on Twitter more than men did. Unsurprisingly, prominent politicians had a higher average in-degree, meaning that they received more mentions on Twitter than non-prominent politicians. Prominent politicians had high node influence relative to their neighbours (eigenvector centrality), and alongside men politicians, were highly central in the entire network (closeness centrality).

Other network statistics, which capture centrality of nodes in a network according to different metrics, show that women politicians were near nodes in dense network regions (component number, modularity class), and often acted as 'bridging' nodes between those dense regions (betweenness centrality). The latter result is likely skewed towards women because of woman politician Inna Sovsun, an outlying node whose out-degree was 2,250, which was over four times higher than the second highest out-degree for a politician, Oleksiy Goncharenko (out-degree=452) (see Figure 2).

Overall, the analysis for RQ3 indicates that women made more use of Twitter's interactive affordances by mentioning more people, while prominent politicians were highly influential relative to their neighbours.

Average Network Statistics for politicians according to Gender and Prominence					
Network Statistic	All politicians (n=73)	Women (n=25)	Men (n=48)	Prominent (n=13)	Not Prominent (n=60)
In-degree	3.260274	3.32	3.229167	8.461538	2.133333
Out-degree	112.3699	192.56	70.60417	124.1538	109.8167
Degree	115.6301	195.88	73.83333	132.6154	111.95
Component Number	0.027397	0.04	0.020833	0	0.033333
Eigenvector Centrality	0.073809	0.077359	0.071959	0.211094	0.044063
Eccentricity	3.191781	4.84	2.333333	2.538462	3.333333
Closeness Centrality	0.582469	0.479813	0.635936	0.647779	0.568319
Betweenness Centrality	3204.082	5753.886	1876.059	2676.953	3318.294
Modularity Class	9.643836	9.48	9.729167	6.384615	10.35

Table 6: Average network statistics according to gender and prominence.

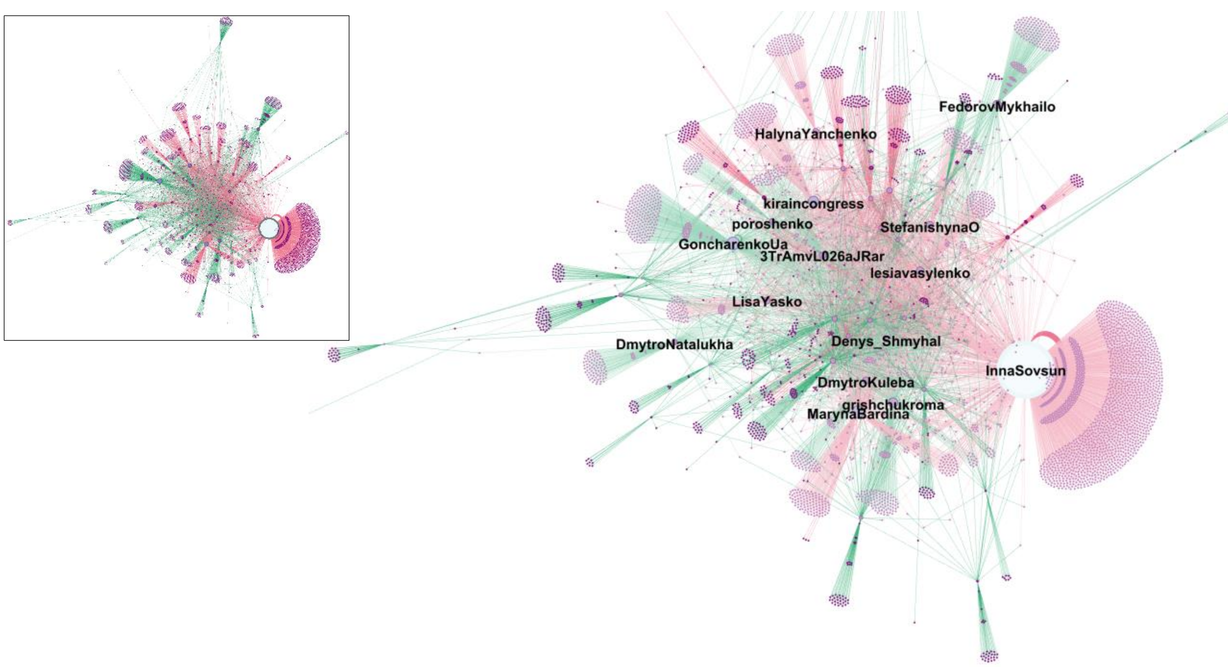

Figure 2: Network visualization of mention (@) interactions by politicians on Twitter (top left), with usernames of 15 accounts with the highest out-degrees labelled (main). Women's interactions are coloured in pink, men's interactions are coloured in green. Nodes with high our-degrees are white, nodes with low out-degrees are purple.

RQ3b: Who are the most engaged-with Twitter accounts by women and men politicians during wartime?

As can be seen in Table 7, three of the top 20 mentioned users by Ukrainian politicians on Twitter were Ukrainian politicians and the Twitter account for Ukrainian parliament, while the other 17 Twitter accounts were all Western politicians, and security or government bodies.

Twitter Username	Total In-degree	In-degree from women politicians	In-degree from men politicians
ZelenskyyUa	36	15	21
NATO	32	12	20
BorisJohnson	32	17	15
POTUS	30	15	15
vonderleyen	27	13	14
DmytroKuleba	25	11	14
AndrzejDuda	24	9	15
EU_Commission	24	9	15
Europarl_EN	24	11	13
EmmanuelMacron	23	13	10
EP_President	23	12	11
ua_parliament	23	13	10
UN	21	9	12
verkhovna_rada	21	9	12
eucopresident	20	10	10
antonioguterres	19	9	10
OlafScholz	19	9	10
trussliz	18	10	8
BWallaceMP	18	10	8
Bundeskanzler	17	9	8

Table 7: Twitter users with highest in-degrees, with a breakdown of in-degrees by women and men politicians.

Discussion and Conclusion

The Women & Peace Hypothesis is inconclusive on the degree to which the salience of war overpowers gendered stereotypical expectations. This study found that women politicians tended to discuss more optimistic war-related topics than men, publish calls for support from the West, promote their presences on social and television media. While there was no evidence of passive views by women, or any calls for compromise, women did appear to reference military and aggressive terms less than their male counterparts did. Men politicians were more likely to overtly call Russia the aggressor on social media and discussed the military and sanctions. Men used hashtags such as #FightLikeUkrainian on Twitter, named types of tanks, missiles, and aircraft, and used verbs such as “fight” and “defend” in topics that were more likely to be used by men than women. This finding partly satisfies the Women & Peace hypothesis in the sense that women were less likely to discuss the military and aggression.

The discussion of cultural topics by both women and men was of interest to this study, as women are expected to be the bearers of Ukrainian culture and morality during both war and peacetime (Rubchak, 2009). Ukrainian culture topics were found to be discussed across social media platforms, genders, mainly before the war, and by both prominent, non-prominent, pro-European and pro-Russian politicians. This means that Ukrainian culture is not purely something that women must uphold in Ukrainian society. However, this may have been the case here because of the salience of Ukraine's Eurovision Competition win.

Women made more use of Twitter's interactive affordances by mentioning more people, while prominent politicians were highly influential relative to their neighbours. This finding matches previous research on gendered interaction strategies during election cycles (Meeks, 2016).

Twitter was found to be a platform where politicians recognized the potential to communicate their country's needs with the West through calls for support and sanctions (RQ1). Between the non-wartime and wartime periods, the proportion of Twitter use by women politicians increased from 10% to 49%, and English language tweeting increased from 21% to 79%. The importance of Twitter during wartime was exemplified by the finding that all non-Ukrainian top-mentioned Twitter accounts by both women and men politicians were Western leaders and organizations (RQ3b), and that women had higher average out-degrees and acted more as bridging nodes than men (RQ3a). Women are expected to seek compromise and collaboration during conflict (Tessler et al., 1999). This study found that while women were collaborative in the sense that they seek Western partners to end the war in their country, but neither men nor women politicians sought any forms of compromise with Russia on Twitter. Politicians were in fact more likely to call Russia the aggressor, call for support from the West, and discuss people affected by the war on Twitter (RQ2b).

Facebook, on the other hand, was likely already a platform where politicians communicated with their constituents, given that activity on Facebook according to gender and language appeared to remain proportionately stable between the non-wartime and wartime periods (RQ1). Politicians likely already had strong Ukrainian audiences on their Facebook profiles and may only have needed to increase the number of updates they provided towards their constituents, rather than changing the audiences they reached out to. They may not have seen Facebook as a platform where they could further their new wartime political goals (calls for support, sanctions) with new audiences. This finding was also exemplified by the finding that government affairs and infrastructure topics were more likely to be discussed on Facebook (RQ2b).

A limitation of this study is that some subsets of data (i.e., non-wartime posts on Twitter) are small and may not have been well reflected in the topic models. To overcome this limitation, a larger time-period of pre-wartime may be selected (i.e., eight months instead of four months).

This study brings to light the nuances of gendered communication during wartime, adding colour to knowledge on the Women and Peace Hypothesis and on Ukrainian political communication. A natural extension of research on what women and men politicians *say* on social media is studying what politicians *get back*, in the form of online abuse and incivility. Future research based on this article will study the types of abuse Ukrainian women and men politicians have received during peace and wartime and measuring whether certain forms of online attacks are more likely to dissuade women or men politicians from participating in online discourse than others.

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Appendix

Posting patterns over time

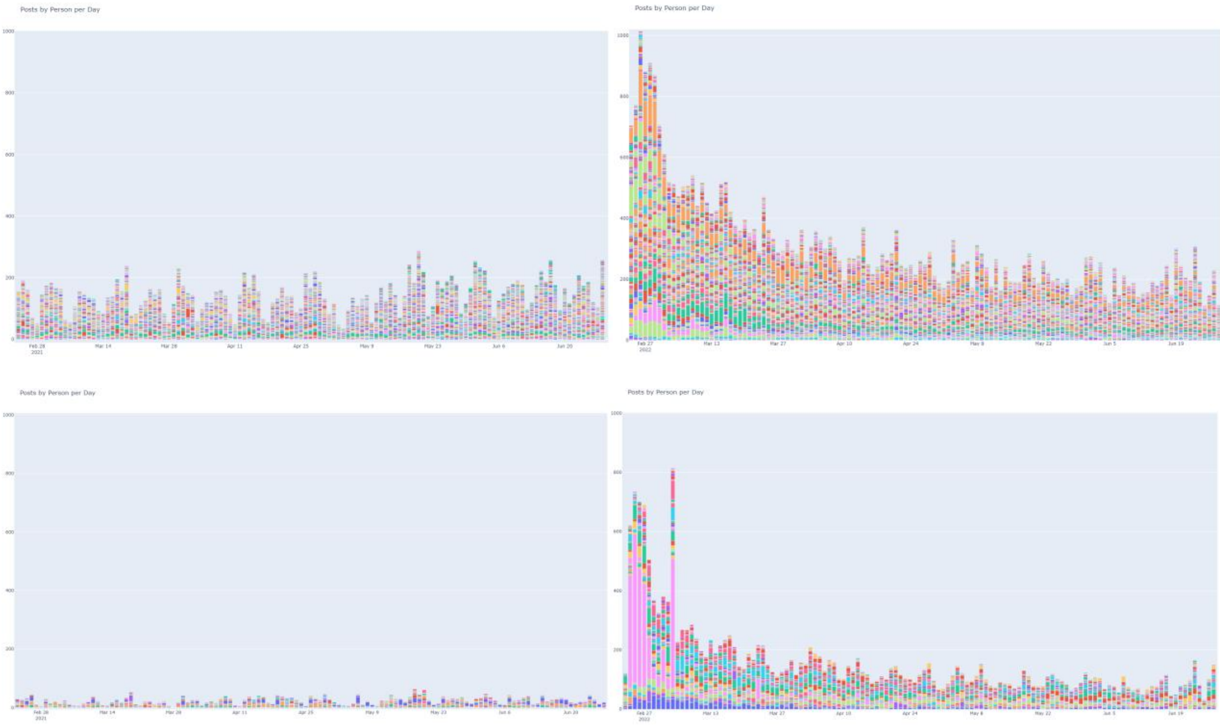

Figure 3: (top left) Non-wartime Facebook posting. (top right) wartime Facebook posting. (bottom left) Non-wartime Twitter posting. (bottom right) wartime Twitter posting (Inna Sovsun in pink). There was more FB posting to begin with, and levels have almost returned to pre-war levels. On twitter, there was a huge spike and conversion to English-language tweeting which remains above pre-war levels.

Model 70 outputs

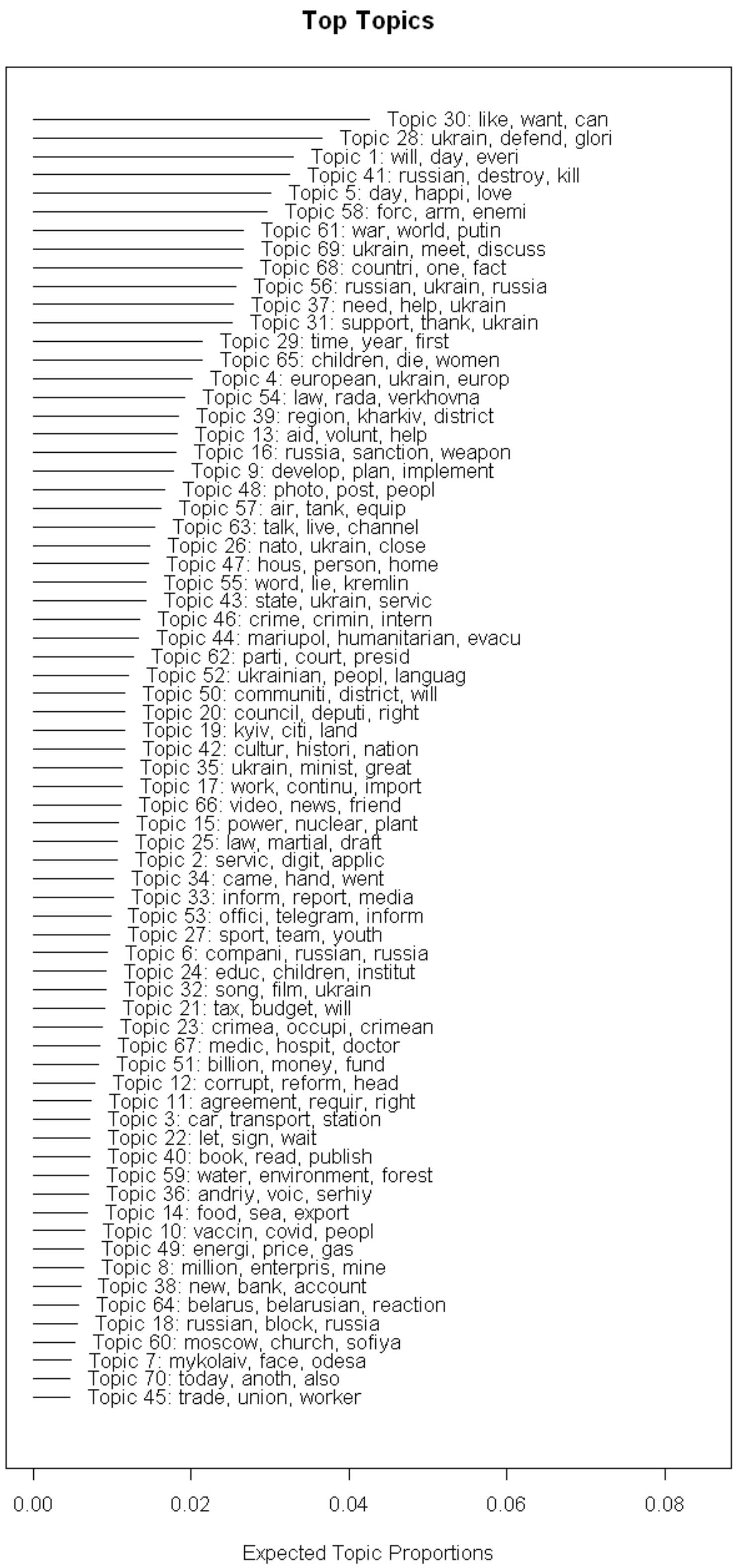

Figure 4: Structural Topic Model output, top terms in topics ordered by expected topic proportions.