Twitter Metrical Data Analysis Using R: Twiplomacy in the Outbreak of the War in Ukraine

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Keywords: The Russian-Ukrainian War, Social Networking Analysis, Data Analysis, Content Analysis, Interactivity Networks.

Abstract: It is common practice for Social Media to be used to inform and sway public opinion during contemporary conflicts. This study focuses on how Twitter (now known as X) was used with regards to the Russian-Ukrainian war during the first three months following Russia's invasion of Ukraine on February 24, 2022. Thirty accounts in total—fifteen from each opposing side—were used to mine the data. The information released by these accounts throughout this monitoring period, along with the frequency of their postings, were collected and investigated in order to highlight the diverse approaches in this kind of cyberspace confrontation. In order to emphasize the key components of each party's strategy and its efficacy, the interactivity networks of the accounts under discussion were constructed and visually analysed. Overall, this research attempt exploits a combination of effective data analysis approaches including word frequencies' investigation and interactivity networks analysis based on the modularity community detection algorithm. By exclusively using Open Source software, the results visually highlight the degree of coordination and intensity of Twitter use of the Ukrainian side, a fact that is in full accordance with the comparatively more successful induced influence Ukraine achieved during this time frame, as this has been reported by the media generally.

1 INTRODUCTION

The full-scale Russian invasion of Ukraine on February 24, 2022, was the most momentous development in the Russian-Ukrainian war since the annexation of Crimea in 2014. This invasion, with state and non-state actors meddling with the information stored or transmitted, has been called the first totalitarian Social Media war, or alternatively, the first totalitarian cyber war and the first hacker war.

It was obvious that both sides would take advantage of the participatory Internet's enormous capacity to launch public awareness campaigns and, eventually, carry out their military goals (Smith, 2019). Social Media gave Ukraine the means to share disjointed information about how the war was fought, which in turn gave Internet users all around the world a mosaic of informational data, establishing, at the same time, the framework for requesting outer assistance. On the other hand, Social Media was seen by Russia as an additional medium for shaping and disseminating the idealized narrative of the conflict.

Ukraine presented the incident as a brutal act of war in general, portraying Russia as the aggressor breaking international law and Ukraine as the defendant attempting to reclaim the area that the invader had taken. Nonetheless, Russia claimed that the events were a deliberate military action to liberate a Russian minority that had been "imprisoned" in the Donetsk and Luhansk regions of Ukraine (Al Jazeera, 2022).

This study analyzes data from the communications patterns spread worldwide by both parties on Twitter (now known as X), a social networking site with 432 million monthly active users as of 2022 (Dixon, 2022), using open source software packages. Twitter has always been a widely used platform for deploying politics and diplomacy (Twiplomacy) worldwide. By using data analysis techniques as well as statistics, the study's goals were to analyze the spoken communications exchanged

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Vagianos, D. and Papatsas, T.
Twitter Metrical Data Analysis Using R: Twiplomacy in the Outbreak of the War in Ukraine.
DOI: 10.5220/0012812400003756

In *Proceedings of the 13th International Conference on Data Science, Technology and Applications (DATA 2024)*, pages 494-504
ISBN: 978-989-758-707-8; ISSN: 2184-285X

during the three months that followed Russia's invasion of Ukraine on February 24, 2022, to document the tactics used by both sides as well as the degree of coordination in the way that different accounts used the platform, and, lastly, to assess how successful each side was in electronic diplomacy over this field of confrontation.

2 RELATED WORK

Throughout their nearly two decades in cyberspace, Social Media have been utilized to investigate social concerns through the application of techniques from the ever developing data science field. Furthermore, a well-liked natural language processing (NLP) method that academics have employed in a variety of fields is content analysis. The method is frequently applied in studies on Twitter because of the platform's nature as a microblogging service.

Younis, for instance, employed the 'afinn' dictionary approach to determine people's opinions about data obtained from Twitter about two UK stores (Asda and Tesco) over the 2014 Christmas season (Younis, 2015). Similar text processing on Twitter data were applied by Kabir et al. using R (Kabir et al., 2018). By tracking word usage rates, they demonstrated how positive and negative words influenced respondents' overall sentiment in a variety of qualitative surveys by using R over Twitter data. Arun et al. analyzed tweets in India that discussed people's opinions regarding the delegitimization process using the Bing dictionary technique (Arun et al., 2017). Saini et al. (2019) employed a similar technique of categorizing impact of tweets concerning healthcare and illnesses into ten groups using the "nrc" lexicon.

Furthermore, R Studio and Gephi have shown to be outstanding resources for a variety of data science applications. For instance, Koutsoupias and Mikelis used R Studio and text mining software to review international relations materials in order to look for recurring, related terms (Koutsoupias and Mikelis, 2021). Taking centrality into account when computing their metrics, Wajahat et al. gathered data from Netvizz's Facebook API and visualized Facebook social networks linked to the official CNN profile page using Gephi (Wajahat et al., 2020). Zhu et al. conducted content analysis on a Reddit dataset regarding the Russian-Ukrainian war using R studio visualization techniques (Zhu et al., 2022). Using data from the Reddit platform, Hanley et al. examined Russian media narratives targeted at English-speaking customers using the MPNet model and a semantic search algorithm (Hanley et al., 2022). Using specified keywords and hashtags to track statistics, Haq et al. examined the text of around 1.6 million tweets obtained via the Twitter API during the first week of escalation (Haq et al., 2022).

Using a bigger dataset (57.3 million tweets, 7.7 million users), Shevtsov et al. investigated the frequency of tweets in the Russian-Ukrainian War (Shevtsov et al., 2022). In an analysis of tweets from December 31, 2021 to March 3, 2022 of the same war, Agarwal et al. used the "bing" dictionary. Finally, Džubur et al. employed the RoBERTa-LSTM technique for sentiment analysis by studying hashtags and users. They also mapped semantic, interactivity networks of various profiles using Gephi for their network analysis (Džubur et al., 2022).

3 METHODOLOGY

This study focused on the first 3 months after Russia's invasion of Ukraine. This decision was made because the situation in Ukraine was totally unstable at the time, a fact that was reflected by the numerous tweets that captured the overall tone of hostility. Thirty Twitter accounts were selected for use, with fifteen accounts for each country, due to the volume of data that was accessible. The following criteria were used to choose the accounts:

i. English written tweets. Tweets written in Russian or Ukrainian might be directed towards those who speak those languages, but tweets written in English undoubtedly target a larger audience.
ii. The account holder needs to be well-liked on Twitter and a recognized expert on this conflict. Politicians were carefully chosen for our sample along with news media, political analysts, consultants, ministries, and other prominent figures with a sizable following basis and impact.
iii. "Official accounts" or "affiliated media". With consistent tweets in support of an account, Twitter labels them as such.

Table 1: Selected Ukranian Twitter accounts Study Group.

Account	Description
ZelenskyyUa	VolodymyrZelenskyy, President of Ukraine
Ukraine	Official Twitter account of Ukraine
lesiavasylenko	Lesia Vasylenko, Ukrainian MP
Denys_Shmyhal	DenysShmyhal, Prime Minister of Ukraine
StefanishynaO	OlgaStefanishyna, Deputy Prime Minister of Ukraine
FedorovMykhailo	MykhailoFedorov, Deputy President of Ukraine
DmytroKuleba	DmytroKuleba, Minister for Foreign Affairs of Ukraine
oleksiireznikov	OleksiiReznikov, Minister of Defence of Ukraine
otkachenkoua	TkachenkoOleksandr, Minister for Culture of Ukraine
Podolyak_M	Advisor to the Office of the President of Ukraine
NewVoiceUkraine	The top independent English-language news in Ukraine
MFA_Ukraine	Official Twitter account of the Ministry of Foreign Affairs of Ukraine
SergiyKyslytsya	SergiyKyslytsya, Representative of Ukraine in the UN
UKRinUN	Official Twitter account for Mission of Ukraine to the UN
Makeiev	OleksiiMakeiev, Ambassador of Ukraine in Germany

From the Ukrainian side, the accounts in Table 1 were chosen based on the aforementioned criteria

Table 2: Selected Russian Twitter accounts Study Group.

Account	Description
mfa_russia	Official Twitter account of the Ministry of Foreign Affairs of Russia
Russia	Official Twitter account of the Russian Federation
KremlinRussia_E	Official Kremlin news from the President of Russia
GovernmentRF	Official news of the Prime Minister & the Russian Government
MID_Kaliningrad	Official Twitter account of the Delegate in Kaliningrad
MedvedevRussiaE	DmitryMedvedev, Deputy Chairman of the Security Council of Russia
mod_russia	Official Twitter account of the Russian Ministry of Defence
DnKornev	Russian military journalist and blogger in English
Amb_Ulyanov	MikhailUlyanov, Official Representative of Russia in Vienna
Dpol_un	DmitryPolyanskiy, Official Representative of Russia to the UN
A__Alimov	AlexanderAlimov, Official Representative of Russia to the UN
RussiaUN	Official Twitter account of the Russian Mission to the UN
FridrihShow	NadanaFridrikhson, Russian journalist in English
RusMission_EU	Official Twitter account of the Russian Mission to the EU
politblogme	MariaDubovikova, Russian journalist and analyst in English

The Russian side's accounts were chosen based on the same standards (Table 2). It can be seen even at this early stage of the investigation that relatively more members of the Ukrainian presidential cabinet had Twitter accounts. This pattern became more noticeable when the study's scope was later expanded to cover a larger spectrum of government personnel. It should be mentioned that these accounts usually tweeted in English even prior to the events of 2022. It was more difficult to find Russian presidential office officials—including Russian President Vladimir Putin—who tweeted in English because many of them either posted only in Russian or had no Twitter account at all. Rather, Vladimir Putin seems to be in charge of two accounts, "KremlinRussia" (which tweets in Russian) and "KremlinRussia_E" (which tweets in English), which function in tandem with the profile of the president of Ukraine. Upon initial observation, it was also noted that other Russian government figures with profiles in both Russian and English, shared information more often in English than in Russian.

Lastly, this study focused on two sets of accounts: collaborative journalists participating in the Russian-Ukrainian war, as well as a variety of political entities. Although these entities might not have attended any of the focus groups, this initial selection helped uncover more Twitter accounts owned by significant figures engaged in the conflict. Finally, since the time required to run these programs' calculations grows exponentially with the amount of input data, it was possible to conduct the mathematical calculations with the available software and equipment in reasonable time by keeping the study's sample size limited to these thirty profiles.

Open source software was used for this investigation. R Studio was the primary application utilized because of its ease of use, data mining capabilities and statistical calculations (Kumar and Paul, 2016).

Table 3 lists the extra packages that were used along with their purposes. Using a Twitter account, developer account permissions were granted in order to get the datasets for analysis from the Twitter platform using the “rtweet” package. The search results were restricted to the designated time frame.

An open source network visualization tool named Gephi was also utilized (Bastian et al., 2009), which allowed for the mapping of the interactivity network between the chosen accounts and the identification of the most significant nodes, based on how frequently they appeared in tweets.

Table 3: Selected R Studio packages.

Package	Description
rtweet a	Main data mining tool from Twitter
tidyverse	Set of functions for graphing and data processing
tm	Natural language text mining functions (nl)
dplyr	Data manipulation functions
TSstudio	Time series visualisation functions
forestmangr	Functions for data frames and calculations
ggplot2	Functions for creating customized graphs

3.1 Tweets’ Text Analysis

Using the R Studio "tm" package, Twitter posts were converted into .txt files to make it feasible for unnecessary data to be removed (Feinerer et al., 2008). The following ensuing interventions were executed:

i. All uppercase characters were changed into lowercase, due to the software's sensitivity to this issue.
ii. All non-English terms found in the tweets from the chosen accounts were disregarded in this analysis.
iii. Punctuation marks such dots, commas, exclamation points, etc. were removed from the texts under study.
iv. Numbers were removed from the analysis. They were only taken into account when they contained crucial information in combination with nearby words. For instance, the number "170" is semantically useless but when paired with the words "casualties" or "refugees," it might provide important information.
v. Symbols like €, £, TM, ", â, /, @, ®, _, -, and others that were present in emojis, hyperlinks etc. were eliminated. In order to achieve this, a function in R was developed to change these superfluous symbols into spaces, which were subsequently removed.
vi. Prepositions, conjunctions, Emojis, Cyrillic sentences and numbers made up the majority of the words that were eliminated.
vii. Terms with comparable meanings were grouped together without using any dictionary. For instance, the terms "ukrainian," "ukrainians," and "ukraines," were transformed into "ukraine" in a manner similar to that of symbols; conversely, the words "neonazi," "neonazis," "nazism," "nationalists," and "azov" were converted to "nazi," and so forth (depending on their meaning). By converting these terms, the software accurately categorized the words rather than breaking them up into smaller groupings. Multiword expressions and word embeddings were not considered in this approach.
viii. Since the gaps had no bearing on the text, they were removed.

To determine the minimal frequency of word occurrence, the revised text was used. By converting the text files into a tabular format and presenting the term in one column and its frequency in the adjacent column, the words were summed up in two columns. These tables were sorted in decreasing order using the "ggplot2" package, and each country's most frequent words were displayed as a bar chart that showed the overall volume and ranking of these words.

3.2 Twitter Interactivity Networks

The next stage was to mine the data required to build each focus group's interactivity network. Using the "dplyr" software, two .csv files were made for each nation (—one containing the connections and the other containing the nodes). These files were used as Gephi's input data. Then, in order to build the interactivity networks in Gephi, the following parameterizations were applied to guarantee a better visual presentation and to increase the accuracy of the computations:

i. Self-loops: A lot of accounts frequently made self-referential statements or retweeted their own tweets. As a result, the network nodes' in-degree weight grew, making them more significant than they are. These cases ought to be disregarded.
ii. Network directionality: it was important to specify the references’ direction.
iii. Nodes were scaled by the weight of the weighted in-degree references: this allowed for identifying significant nodes (Ayyappan et al., 2016).

iv. The modularity community detection algorithm was used to highlight the accounts' communities in the networks, based on their connections (Newman, 2006).
v. Yifan Hu network creation: this method highlighted the important central accounts in the network and allowed for its effective and clear visualization (Hu, 2004).
vi. Each network's visualisation was done in two stages, which guaranteed that the interactivity networks would be effectively visualized. The labels of the fifteen selected profiles remained after the first stage, which involved the removal of nodes with a single incoming reference (in-degree=1). The visible accounts and the labels of the accounts with the highest degree of incoming references were plotted in the second stage, after the labels displayed in the first stage were hidden and the filter was increased by one (2 ≤ in-degree).

Four schemes were developed, two for each focus group, using these criteria.

4 APPLICATION OF THE METHOD AND EXTRACTION OF RESULTS

The first significant finding in this research was that there were fewer tweets by the Russian side during the analysis period. Specifically, the Ukrainian side released twenty-five percent more content. The top 50 terms used on each side during these posts are shown in Figures 1 and 2.

It can be observed that terms like "war," "support," "world," "aggression" of the opposing side, "Kiev," and appeals for assistance to "standwithukraine" are among the top ten terms used on the Ukrainian side. 'War' was the third most frequent term.

From this observation, one can conclude that Ukraine's posts aim to inform and sensitize the world by emphasizing the aggression of the invader and therefore make direct or indirect appeals for support by the international community.

Comparably, "Nazi" is the third most used word in Russia's top ten list of words, which also includes "military," "war," "Kiev," and "civilians" (Figure 2). The latter provides a clear image of the Russian side's communication strategy regarding the reasons behind the invasion, as evidenced by the tweets it posted.

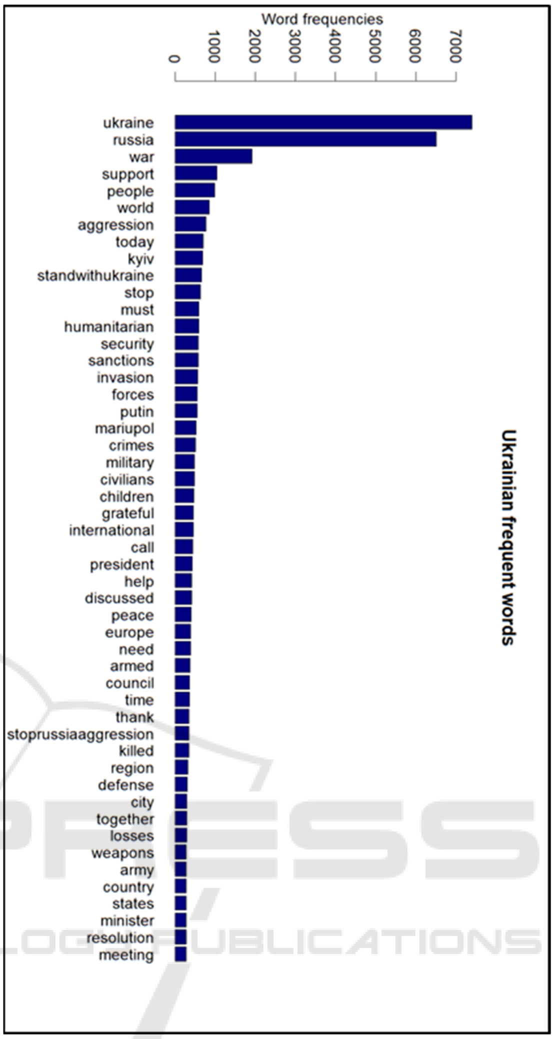


Figure 1: 50 Most frequently used words in the tweets of the Ukrainian side.

In Figure 1, one can see that the Ukrainian side utilizes phrases with a warlike meaning, such as "invasion," "defence," "forces," "peace," "killed," "crimes," and "children," in order to incite animosity toward the aggressor. Additionally, the terms "resolution," "sanctions," and "meeting" signal to the global community that action is needed. Geographically speaking, the terms Mariupol and Kiev feature prominently on the list; references to Europe are also common, either in regard to their potential support or their role in mediating the crisis. In an effort to start movements in favor of Ukraine, the hashtags "stoprussiaaggression" and "standwithukraine," which rank 10th and 11th respectively, were also widely used. Specifically, on February 25, 2022, the hashtag "standwithukraine" was included in over 40000 tweets (GetDayTrends, 2022).

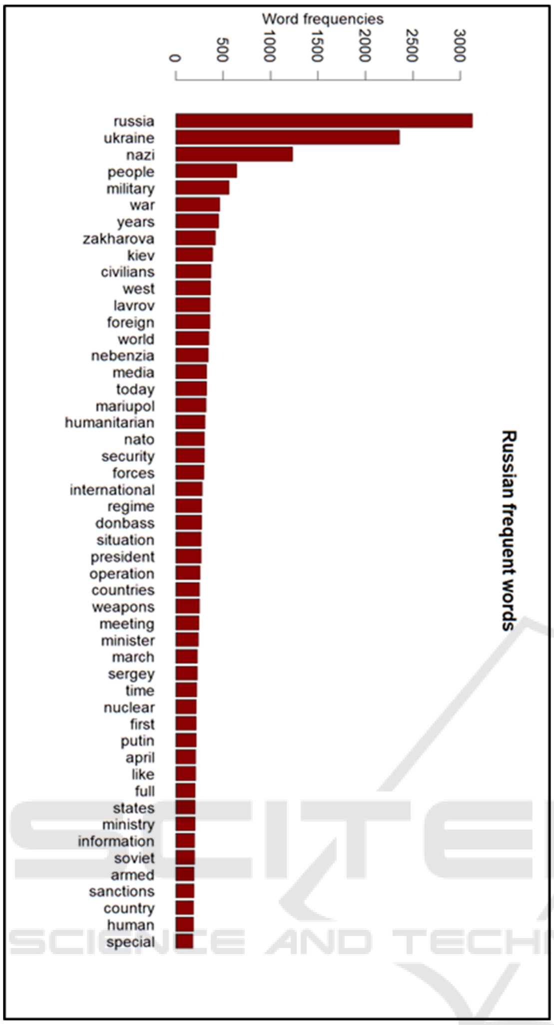
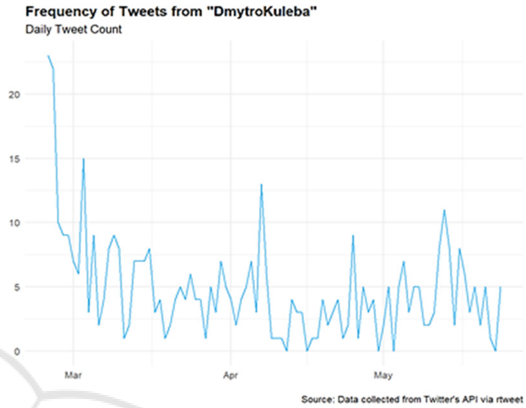


Figure 2: 50 Most frequently used words in the tweets of the Russian side.

One may observe that there are differences in the subject areas and style by comparing Figures 1 and 2. "West" was the eleventh most frequently used word, highlighting Russia's position on the political front established by the West. Political terms and names like "Putin", "Lavrov", "Zakharova", "Nebenzia", and "Sergey" are used in large groups of tweets, along with terms like "international", "countries", "states", and "NATO". This shows how the Russian side uses Twitter for news, information, and e-diplomacy. Additionally, the descriptions of the events are given a more official colour by the terms "operations," "security," "situation," "civilians," and "humanitarian," which contrasts sharply with how the opposite belligerent side makes these same descriptions. The towns of Mariupol and Kiev are the most commonly stated geographical regions here, although "Donbass" has also continued to be mentioned regularly, presumably as a result of the events that occurred there. Generally speaking, the Russian side uses more words related to a wider range of mostly informative content, whereas the Ukrainian side alternates between political and humanitarian news and war narratives with a specific colour tone.

The official "DmytroKuleba" account of the Minister for Foreign Affairs of Ukraine, the official "ZelenskyyUa" account of President Volodymyr



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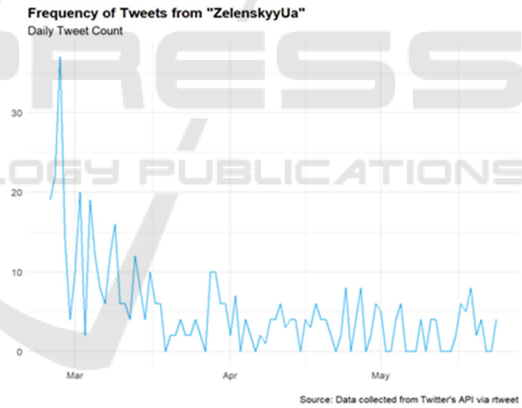

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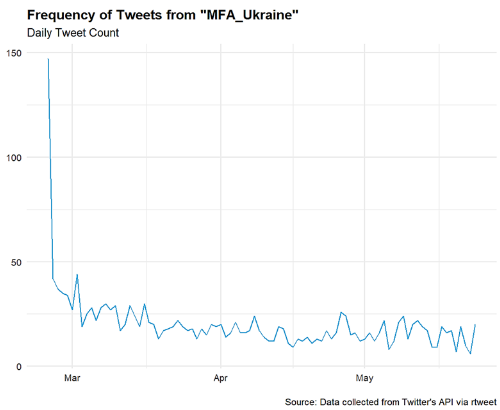

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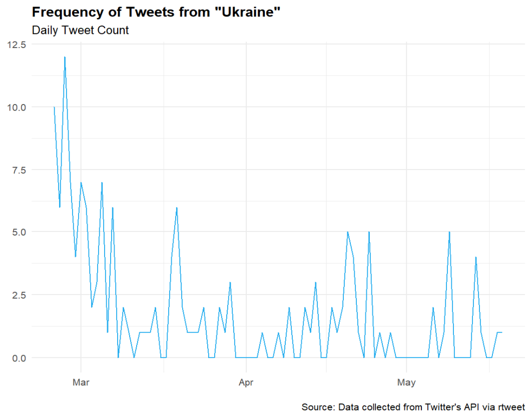
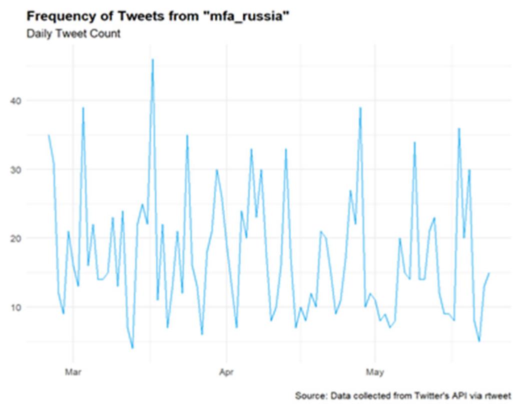


(d)

Figure 3: Frequency of posts from 4 selected Ukrainian Twitter accounts.

Zelenskyy of Ukraine, the official "MFA_Ukraine" account of the Ministry of Foreign Affairs of Ukraine, and the "Ukraine" account, correspond to the four charts of Figure 3 that indicate the frequencies and total posts of four representative accounts of the Ukrainian side during the period under review. The four charts highlight the high activity in the initial days of the invasion as well as the constant high frequency of posts in this time frame. Furthermore, the four accounts' variance lines visually exhibit qualitative similarities, indicating a probable coordination in their activities and, as a result, a methodical posting strategy.

The four charts in Figure 4 depict the indicative frequencies and total posts of four representative Russian side accounts during the same period: the Russian Ministry of Foreign Affairs' "mfa_russia" account, the Ministry of Defense's "mod_russia" account, the Representative's "MID_Kaliningrad" account, and the Russian Mission to the UN's "RussiaUN" account. Comparing the four charts, it



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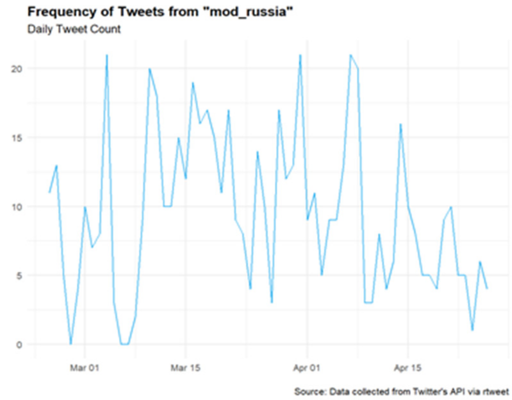

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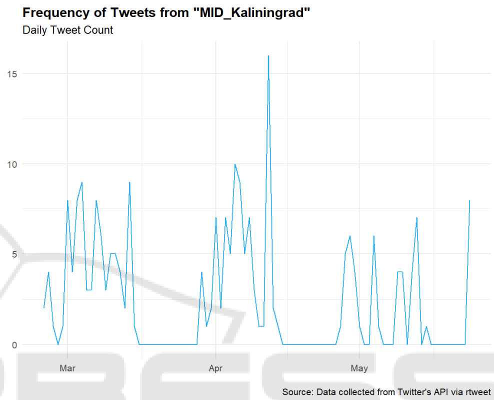

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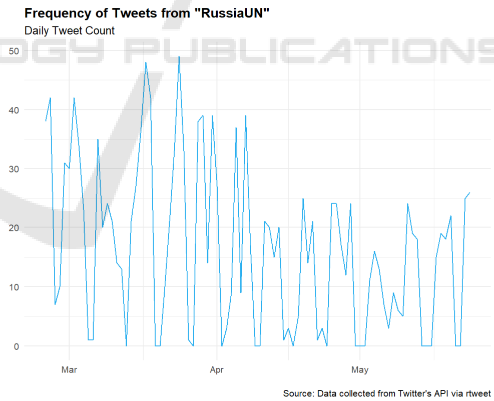

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Figure 4: Frequency of posts from 4 selected Russian Twitter accounts.

can be noted that the frequency of posts is lower than the ones on the Ukrainian side. Thus, this quantitative approach demonstrates that the Ukrainian side's engagement has been more rigorous as well as more intensive, which is consistent with the greater influence that Ukraine appears to have had—both during and after the invasion—on Social Media, a fact that has also been reported by the media generally.

Note that the four charts of figure 4 have the maximum qualitative similarity of their curve, much like the four charts of figure 3 that were selected to be given here. The frequency of articles varies significantly amongst the 15 Russian accounts, perhaps because of the relatively poor level of coordination between the political and journalistic organizations managing these accounts. On the other hand, Ukrainian account holders exhibit a stronger link with respect to a widely recognized pattern of posting rate, topic selection, and even word choice in terms of posts throughout this time frame.

The interactivity network graphs of the Ukrainian group's first and second stage accounts, as previously mentioned in the research methodology (modularity detection algorithm), are displayed in figures 5 and 6. The first stage figure 5 shows that the largest and most concentrated nodes of the account network were "DmytroKuleba", "MFA_Ukraine", and "ZelenskyyUa" based on the interactions and their content. The first two are red, indicating that they are part of the same community, and this is always the case based on the modularity detection algorithm that was used. Given that Kuleba is the Ukraine's foreign minister, this appears to support the algorithm's accuracy. Conversely, the accounts "FedorovMykhailo","otkachenkoua", and "Makeiev" appear to have the most dissimilar profiles with their common references and indicated communities, even if they are all governmental accounts. The network exhibits consistency in terms of content and relationships, as seen by the other accounts that were noticed and looked to be key to it. They also appeared to be located close to one another.

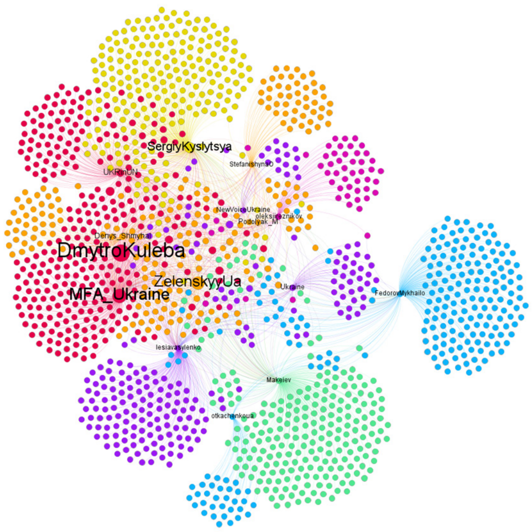

Figure 5: 1st Stage interactivity network of Ukrainian side accounts.

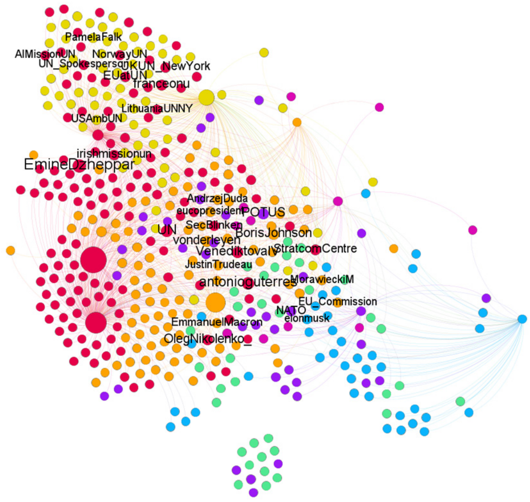

Figure 6: 2nd Stage interactivity network of Ukrainian side accounts.

This research focused on the accounts that were not highlighted in the first stage and displayed the most significant Twitter accounts (Table 4) based on content and the quantity of incoming mentions in the stage 2 interactivity network (Figure 5). Thus, two clusters are formed. While the second was directed at nation-state leaders and the European Union, the first was focused on the United Nations. The first group appeared to represent the culmination of two communities: one associated with international affairs (red) and one with the UN (yellow). In the second, several communities were combined and given a central position inside the network.

Table 4: Accounts highlighted during the creation of the 2nd stage of the Ukrainian side's interactivity network.

Screen name	Description
POTUS	Joe Biden, President of the United States
BorisJohnson	Boris Johnson, Prime Minister of the United Kingdom
VenediktovalV	Ambassador of Ukraine to the Swiss Confederation
SecBlinken	Anthony Blinken, Secretary of State of the United States
eucopresident	Charles Michel, President of the European Council
UN	Official account of the United Nations
AndrzejDuda	Andrzej Duda, President of Poland
NATO	Official account of the North Atlantic Treaty Organisation
antonioguterres	António Guterres, Secretary General of the United Nations
EU_Commission	Official account of the European Commission

Table 4: Accounts highlighted during the creation of the 2nd stage of the Ukrainian side's interactivity network(cont.).

vonderleyen	Ursula Von Der Leyen, President of the European Commission
MorawieckiM	Mateusz Morawiecki, Prime Minister of Poland
JustinTrudeau	JustinTrudeau, Prime Minister of Canada
OlegNikolenko_	Spokesman of the Ministry of Foreign Affairs of Ukraine
UKUN_NewYork	Official account of the United Kingdom's UN office in New York
EmineDzeppar	First Deputy Foreign Minister of Ukraine
AlMissionUN	Albania's official account in the United Nations in New York
irishmissionun	Ireland's official account in the United Nations in New York
USambUN	US Ambassador Linda Thomas-Greenfield to the UN
LithuaniaUNNY	Lithuania's official account in the United Nations in New York
UNspokesperson	Official account of the Secretary General Office of the UN
NorwayUN	Norway's official account in the United Nations in New York
EUatUN	Delegation of the European Union in the UN in New York
franceonu	France official account in the United Nations in New York
elonmusk	Elon Musk, Entrepreneur and investor
UNspokesperson	Official account of the Secretary General Office of the UN

The interactivity networks for the Russian group's first and second stage accounts are displayed in figures 7 and 8.

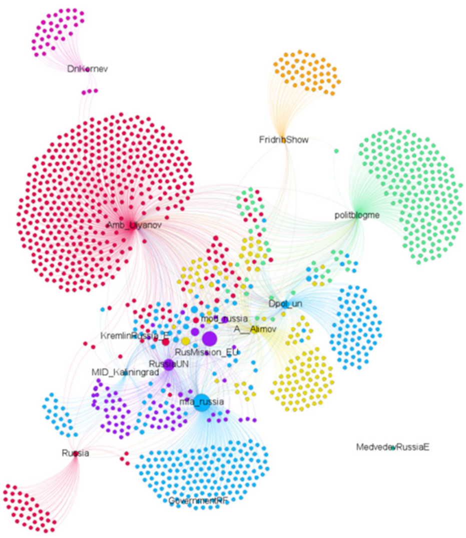

Figure 7: 1st Stage interactivity network of Russian side accounts.

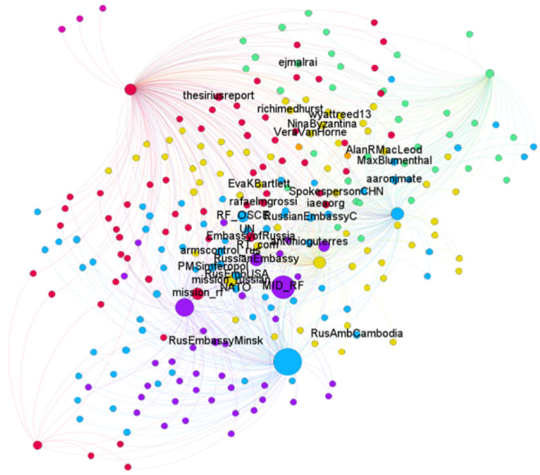

Figure 8: 2nd Stage interactivity network of Russian side accounts.

The network is noticeably less compact in the first stage figure 7, with many of the observed accounts situated far from the centre and forming their own communities. Unexpectedly, "MedvedevRussiaE" is the most estranged account; it has no connections to the entire interactivity network and no relevant community. Being "satellites" to the main network, the "DnKornev," "FridrihShow," and "politblogme" accounts have their own communities, while the "Russia" account is not particularly connected to the other profiles (bottom left of the graph of Figure 7). Despite being a part of a huge community, the "GovernmentRF" account is not regarded as a significant node in that network. The network's core is made up of the other accounts, with "Amb_Ulyanov" displaying a sizable community and several connections to other accounts.

The most significant accounts that surfaced (Table 5) once more established two clusters in the Russian second stage interactivity network (Figure 8). With independent or state journalists, the first was focused on journalism, and the second was focused on international affairs through embassies.

Because of its central location in the original interactivity network, the second community was a composite of several dispersed communities, while the first partially contained three communities (green, yellow, and red). Furthermore, two prominent profile accounts regarding the International Atomic Energy Agency were noted in the centre ("iaeaorg" and "rafaelmgrossi"). Their presence in this network can be correlated with the content analysis of the posts, since "nuclear" was one of the most frequently used terms in the Russian group (Figure 2).

Table 5: Accounts highlighted during the creation of the 2nd stage of the Ukrainian side's interactivity network.

Screen name	Description
ejmalrai	Journalist, war correspondent in Asia
thesiriusreport	Independent International Relations Analysts
rihimedhurst	Syro-British freelance journalist
wyattreed13	Russian war correspondent
NinaByzantina	Russian journalist and international relations analyst
VeraVanHorne	Russian-Canadian journalist
AlanRMcleod	Independent Journalist at "MintPressNews"
MaxBlumenthal	Independent journalist of "TheGreyZonenews"
aaronjmate	Journalist and Podcaster at "The Grey Zone news"
EvaKBarlett	Independent journalist in Donbas
SpokespersonCHN	FA Assistant Minister and representative of China
iaeaorg	International Atomic Energy Agency (IAEA)
rafaelmgrossi	Director General of the IAEA
RF_OSCE	Mission of the Russian Federation to the OSCE
RussianEmbassyC	The Russian Embassy in Canada's Official Account
EmbassyofRussia	The Russian Embassy in South Africa
armscontrol_rus	Negotiations delegation on security and arms control
RussianEmbassy	Official Account of the Russian Embassy in the UK, London
PMSimferopol	Official Account of the Ministry of Foreign Affairs of Russia in Crimea
RusEmbUSA	Official Account of the Russian Embassy in the USA
mission_russian	Russian mission to the United Nations and International Organizations
MID_RF	Official account of the Russian Foreign Ministry in Grozny
RusEmbassyMinsk	Official Account of the Russian Embassy in Belarus
RusAmbCambodia	Official Account of the Russian Embassy in Cambodia
mission_rf	Russian delegation to international organisations in Vienna

Social Media is well on the way to disrupt the traditional channels and methods of diplomacy (Pop, 2018). Analysis like the one above demonstrate the potential of Social Media and online communities in International Relations, Therefore, the results above can provide useful information that can be further scientifically interpreted by IR scientists.

5 CONCLUSIONS AND FUTURE WORK

The study concentrated on Twitter's impact during the initial three months following Russia's invasion of Ukraine. Fifteen official accounts, one from each of the fighting factions, were chosen as exemplary examples, and their content and frequency of postings were analysed using exclusively Open Source software. The study's findings demonstrated how successfully Ukraine used Twitter to spread information and increase awareness by adding words to content that highlighted the invader's aggression and by creating trending hashtags that made direct or indirect appeals for international support. This finding coincided with the general media image that has been shaped during these 3 months and has been delivered to the international community. News on politics or humanitarian issues as well as combat stories were among the Ukrainian themes. However, Russia employed a wider variety of mostly informative tweets on Twitter along with service-oriented content for news, information, and electronic diplomacy.

In terms of posting frequency, account managers in Ukraine were found to have demonstrated a faster pace, improved inter-administrator's collaboration, and a more methodical approach, which was evident in both the posting rate pattern as well as the word and topic selection.

Focusing on the interactivity networks, the Ukrainian side seemed to have used Twitter to get in touch with the UN and other international or European organizations. In contrast, the Russian side's networking revealed that it aimed to establish a channel of communication with Russian embassies and news organizations affiliated with the Russian state in order to disseminate information favourable to the Russian regime and self-report on events that benefited it.

The investigation above demonstrated how Ukraine used Twitter more consistently and, eventually, more successfully throughout the first three months of the conflict, appearing to have met its objectives by employing the right layered tactics. This was clear from the three axes—text analysis, posting frequency, and interactivity networks—over which the current study of this sample was conducted. More data can be added to this area of study to produce results that are more representative and generalized, but doing so will necessitate more sophisticated computing hardware that can handle the increasing computational demands.

Social networks measurements performed in this analysis have provided useful datasets that can be analysed further using a variety of statistical methods. Moreover, other research techniques that can be applied include the use of semantically more effective NLP approaches combined with sentiment analysis of posting content (Mohammad, 2015) and application of multivariate statistical processing of Social Media data. To draw more thorough conclusions or examine trends in various stages of the conflict, these methods can be applied to other Social Media platforms as well as over more extended time frames.

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