Social Media as a Behavior Depolarizer: Evidence from The Russia-Ukraine Conflict

Abstract

Purpose – Social media has played a pivotal role in polarizing views on the Russia-Ukraine conflict. The effects of polarization in online interactions have been extensively studied in many contexts. This research aims to examine how multiple social media sources may act as an integrator of information, and act as a platform for depolarizing behaviors.

Design/methodology/approach – This study analyzes the communications of 6,662 tweets related to the sanctions imposed on Russia by using textual analytics and predictive modeling.

Findings – The research findings reveal that the tweeting behavior of netizens was depolarized because of information from multiple social media sources. However, the influx of information from non-organizational sources such as trending topics and discussions has a depolarizing impact on the user's pre-established attitude.

Implications – For policymakers, conflict mediators and observers, and members of society in general, there is a need for (i) continuous and consistent communication throughout the crisis, (ii) transparency in the information being communicated, and (iii) public awareness of the polarised and conflicting information being provided from multiple actors that may be bias in the claims being made about the conflict.
crisis.

Originality – While previous research has examined the Russia-Ukraine conflict from a variety of perspectives, this is the first study to examine how social media might be used to reduce attitude polarisation during times of conflict.

Keywords behavior depolarization, echo chambers, Russia-Ukraine conflict, social media, textual analytics

Paper Type Research Paper

Introduction

The pro-Russian war in Ukraine started with Euromaidan demonstrations and the 2014 fall of

President Viktor Yanukovych (D'Anieri and Kuzio, 2019). Unknown Russian soldiers seized

key infrastructure and locations in Ukrainian-controlled Crimea, including the parliament

building. Crimea joined Russia after a controversial referendum. In April 2014, pro-Russian

organizations in Ukraine's Donbas area protested, leading to a confrontation between the

Ukrainian military and Russian-backed rebels from Luhansk and Donetsk (D'Anieri and

Kuzio, 2019; Polityuk and Hunder, 2022; Potočňák and Mares, 2022). In early November 2021,

Russia and Ukraine clashed near Ukraine's border with Russia. At the height of the conflict,

Russia stationed 100,000 troops and assets in Crimea and Voronezh, Kursk, and Bryansk (Mills, 2022). The Russian navy's Baltic and Northern fleets were transferred to the Black Sea for exercises near the Ukrainian border, as were more soldiers in Belarus. In December 2021, US intelligence learned that Russia planned to invade Ukraine in early 2022 (Mills, 2022). Russia's actions are criticized globally. Sanctions are being levied on Russia, military assistance is being sent to Ukraine, and Western allies are discussing how to successfully collaborate in this scenario.

Digital social media played a vital role in communicating the conflict between Russia and Ukraine, they have promoted and intensified destabilization and disinformation (Mejias and Vokuev, 2017). This is a key component of Russia's 'hybrid warfare' strategy (Manko and Mikhieiev, 2018). Previous studies have discovered that online enmity between Ukrainians and Russians can be sustained, if not intensified, via social media (Lange-Ionatamishvili and Svetoka, 2015; Makhortykh and Sydorova, 2017; Mejias and Vokuev, 2017; Zeitzoff, 2017). The proliferation of contentious politics and emotive topics on social media puts into question the concepts of power, trust (Pieters, 2017), proximity (Medaglia *et al.*, 2022; Segev and Boudana, 2022), and responsibility (Helberger *et al.*, 2018). This bombardment of information can lead to 'echo chambers', whereby individuals 'hear their own voice' (Brugnoli *et al.*, 2019; Modgil *et al.*, 2021), and individuals may express dissent through their social media platform. This polarization may be observed in a variety of conflicts, including the ongoing conflict between Russia and Ukraine. Individuals who are immersed in echo chambers are exposed to information or beliefs that support and strengthen their own (Sunstein, 2002). An echo chamber may distort one's perspective, making it harder to understand and engage in challenging arguments and disagreements. A lack of knowledge, a skewed viewpoint, and a preference for one's own point of view are the three most common causes of prejudice. "Framing" occurs when one person makes a point and everyone else agrees on it. Our choices

are influenced by how information is presented to us (Guo *et al.*, 2015; Holford *et al.*, 2022; Kaye *et al.*, 2015). Nikolayenko (2019) analyzed the public reaction during Peace March held in Moscow on 21 September 2014 on Twitter with the trending hashtag #PeaceMarch. The research found that two groups of differently polarised views i.e. (i) one group referred to as the peace activists assumed the role of individuals with elevated ethical principles and a significant degree of national loyalty, censured the Russian administration for its military involvement in Ukraine, and advocated for a nonviolent resolution to the conflict, (ii) On the other hand, those who opposed the march perceived themselves as genuine patriots while viewing their opponents as betrayers of the nation. They refuted the notion of Russia's military involvement in Ukraine and instigated an assault on individuals who expressed dissent towards Russian foreign policy. More people will be persuaded if others have the same or similar views. Later, the echo chamber is constructed, and the same voice is broadcast and echoed back to the original source, thus magnifying the intensity, and distorting the original experience. However, studies have shown that building echo chambers has a detrimental impact on social media, increasing disinformation, causing gender inequities, and polarizing political parties (Barberá *et al.*, 2015; Geiß *et al.*, 2021; Guess, 2021; Koiranen *et al.*, 2022). The latter event is exacerbated if the political character of the topic intends to further polarize its audience. More importantly, if individuals accept disinformation, it may have real-world implications (Naeem and Ozuem, 2022). The research suggests an approach for preventing the establishment of echo chambers in the online community and depolarizing those that have developed by recognizing and deploying nano-influencers at certain hotspots, hence increasing cross-community interaction. In the context of this study, online communities are "networks of social media users connected by information sharing, conversations, or other forms of communication" (Zhen *et al.*, 2022, p. 2).

Previous studies on social media as a tool for information dissemination and attitude formation concerning the discussions about Russia Ukraine conflict have tried to unearth strategies to discourage the propagation of false information (Doroshenko and Lukito, 2021; Duvanova *et al.*, 2016; Golovchenko, 2022; Khaldarova and Pantti, 2016; Kozachenko, 2021; Mejias and Vokuev, 2017). Seeing the rise of disinformation in the online ecosystem, Haurter (2021) proposed a digital forensic process tracing to investigate the causes of the war. The author is of the view that an in-depth investigation of open-source intelligence could lead to the identification of partisan and non-partisan sources of information along with various critical information related to the situation of war thus calling for further research to mitigate the growing concern of misinformation in the digital information sources.

Based on the research directions proposed by several researchers (Duvanova *et al.*, 2016; Golovchenko *et al.*, 2018; Hauter, 2021; Nikolayenko, 2019), this study examines the communications taking place on Twitter concerning the sanctions imposed on Russia and attempts to answer the following research questions (RQs):

RQ1: What is the general semantic polarization of users toward the Russia-Ukraine Conflict?

RQ2: What are the attributes that lead to polarization or de-polarization of attitudes on Twitter?

Based on the insights obtained by analyzing the conversations over Twitter, the study suggests for the employment of nano-influencers by organizations, governments, and practitioners as a countermeasure to prevent the dissemination of misinformation and re-construct the attitude of the public that may have got distorted due excessive consumption of fake news and misinformation. The study is exploratory in nature and unique in the domain of attitude management during the conflict through effective use of digital social media.

The remainder of the paper is structured as follows: A background literature on social media in the context of the Russia-Ukraine conflict is presented. Next, the research

methodology and analytical techniques employed in this study are outlined. Then the results from the predictive modelling and sentiment analysis are reported. Followed by a discussion, implications, limitations, and future research directions. The paper ends with a conclusion.

Background literature to *Information Warfare and Social Media*

Communication and media studies provide valuable insight into how individuals and governments modulate the thinking process and behavioral disposition of the general public in times of crisis. Social media platforms are socio-technical architectures that enable and influence interaction and communication between users (Alaimo and Kallinikos, 2017; Zheng *et al.*, 2015). Exploration of the Scopus database using the query (TITLE-ABS-KEY ('Russia' AND 'Ukraine' AND 'war' AND social media) resulted in 60 articles concentrated on the investigation of information dissemination and attitude formation towards Russia Ukraine conflict over social media. A network diagram of the major keywords and the associations between the keywords is illustrated in Figure 1.
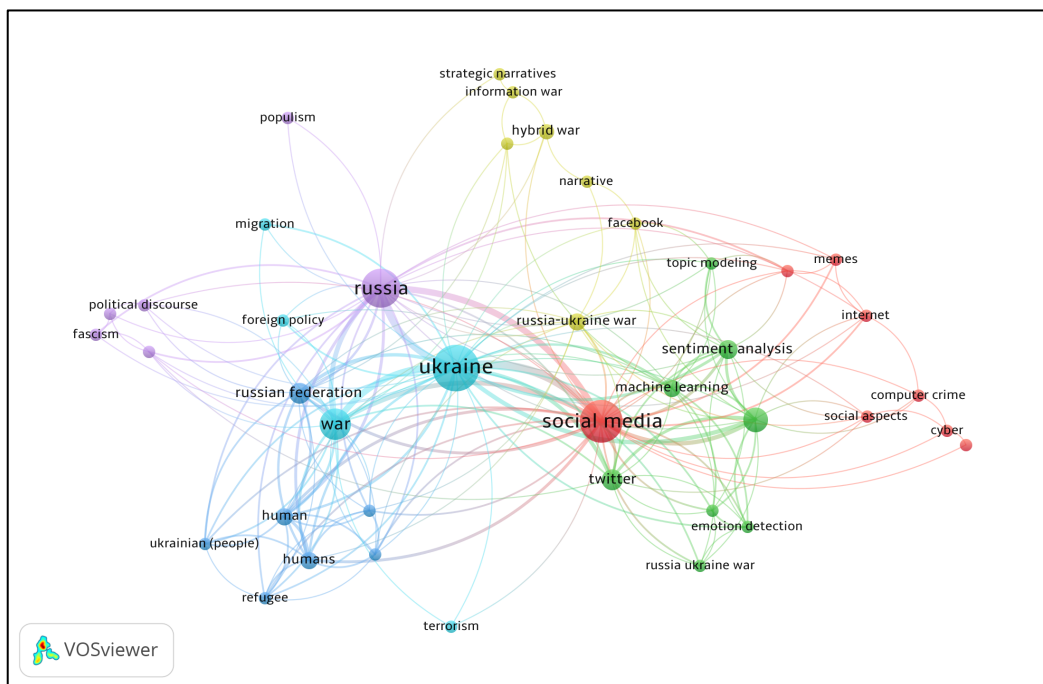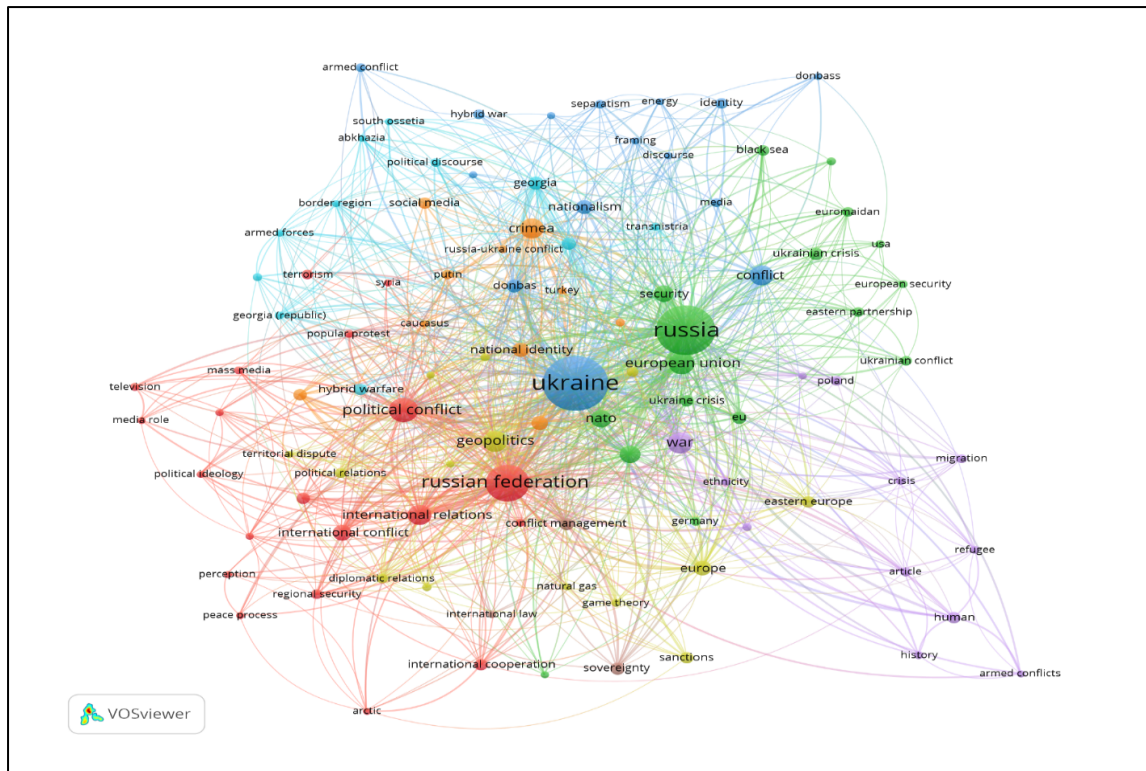

Figure 1. A network diagram based on the query (Russia AND Ukraine AND war AND social media)

The assessment of extant literature indicates that in this historic Russia - Ukraine war, governments, the public, and organizations use all conceivable methods to seek sympathy and support from citizens across countries (Duvanova *et al.*, 2016; Nikolayenko, 2019; Udris *et al.*, 2023). Communications through digital media are often presented with an intended polarity to distort the public's existing emotions and implant new emotions (Barberá *et al.*, 2015; Geiß *et al.*, 2021; Guess, 2021; Koiranen *et al.*, 2022; Makhortykh and Sydorova, 2017). Recent studies have been conducted analyzing the sentiment of communications that have taken place over social media and have outlined the various reasons contributing to a definite semantic polarity. Based on an analysis of one million Facebook posts from users in 108 countries, Ngo *et al.* (2022) concluded that those living in countries to which Russia sends a disproportionately large amount of its exports are more likely to support sanctions against Russia for the invasion. Those from nations that rely substantially on Russian exports, on the other hand, are apparently opposed to the sanctions. The general public's outlook on the conflict is heavily influenced by trade with Russia. Similarly, various other studies have used sentiment analysis as a tool to investigate the public's emotions from various perspectives such as key narratives displayed by users in communications (Maathuis and Kerkhof, 2023; Sazzed, 2022), and the use of bots to influence and polarize the public sentiment concerning Russia/Ukraine conflict (Smart *et al.*, 2022). Golovchenko *et al.* (2018) in their study examined 950,000 Twitter messages and found a multitude of contradictory allegations online after Russia shot down Malaysia Airlines Flight 17 over Ukraine by Higgins and Phillips. The researchers also found high active involvement of citizens in spreading information as well as disinformation. The latest Russian invasion into Ukrainian territory has heightened these attempts, making it increasingly difficult to filter authentic information from the proliferation of conflicting, inflammatory, and almost impossible-to-verify information.

Unlike previous studies on the Russia-Ukraine conflict, this research uses social media analytics to extract data from Twitter to gain insight into the dominating sentiments among netizens in the current Russia-Ukraine conflict. The term "netizen" pertains to an individual who engages in active participation within virtual communities and engages in online interactions with other individuals. The term "netizen" is a linguistic blend of the words "internet" and "citizen" and has been in circulation since the nascent stages of the internet. The origin of the term can be traced back to the publication of the book "Netizens: On the History and Impact of Usenet and the Internet", which was authored by Michael Hauben and Ronda Hauben (1997). The definition of netizen as provided in the book refers to an individual who demonstrates skillful or knowledgeable use of the Internet. Subsequently, the aforementioned phrase has gained widespread usage within the realm of virtual communities, social networking platforms, and the concept of responsible online conduct. The research also uncovers the elements that contribute to the creation, polarization, and/or depolarization of emotions among netizens. Based on the findings, the paper proposes a mechanism for preventing rumor induction and depolarization of netizen attitudes acquired because of misinformation intake.

Methodology

Extant literature shows that both sides of the discussion express themselves in diverse and varied ways. The study conducts an open article search on the Scopus database with the keyword "Russia-Ukraine Conflict" which resulted in 572 journal articles. The network diagram based on the authors' keywords has been generated using Vosviewer software and is shown in Figure 2.

Figure 2. A network diagram based on the keyword "Russia-Ukraine Conflict"

In the context of this study, Figure 2 illustrates how extant literature can be broadly classified into four categories, namely, (i) conflict studies (Krickovic, 2015; Mölder and Berg, 2022; Potočňák and Mares, 2022), (ii) political studies (Crowther, 2011; Mihaylov and Sala, 2018; Stulberg, 2015; Tabachnik, 2020), (iii) business studies (Buzogány, 2016; Casier, 2020; Van de Graaf and Colgan, 2017; Morbee and Proost, 2010; Roman and Stanculescu, 2021), and (iv) media studies (Driscoll and Steinert-Threlkeld, 2020; Gavra and Savitskaya, 2011; Golovchenko, 2022; Kozachenko, 2021; Makhortykh and Bastian, 2022; Makhortykh and Sydorova, 2017; Nedozhogina, 2019).

Previous studies have used qualitative, quantitative, or mixed-method approaches to comprehensively examine the Russia-Ukraine conflict from the aforementioned viewpoints. In contrast, social media has a vast repository of human behaviour, hence presenting novel opportunities for comprehending individuals, institutions, and the broader social fabric. This study utilises social media analytics and textual analysis techniques to get a deeper

comprehension of emerging patterns and themes within the Russia-Ukraine Conflict. Additionally, it aims to explore the unique characteristics of user participation via digital social media platform of Twitter.

Data collection and description

Twitter is a microblogging service in which users send and receive tweets (280-character textual messages). These tweets can relate to real-time events such as political events, tourism, stock trading, and a variety of other events (Ilk and Fan, 2022; Sul *et al.*, 2017). In this study, we were able to collect user comments, hashtags, and screen names using Twitter's APIs. The study used the R Studio package 'twitteR' (Gentry, 2016) to extract tweets and analyze tweets using advanced search by integrating keywords "Ukraine", "Russia", and "Sanction" by using the Boolean operator AND. Ignoring non-English tweets, a total of 6662 tweets were collected from 29 April 2022 to 9 May 2022. The dataset contained 689 organic tweets and 5973 retweets (see Figure 3). The organic tweets were further used for algorithmic evaluation in the study.
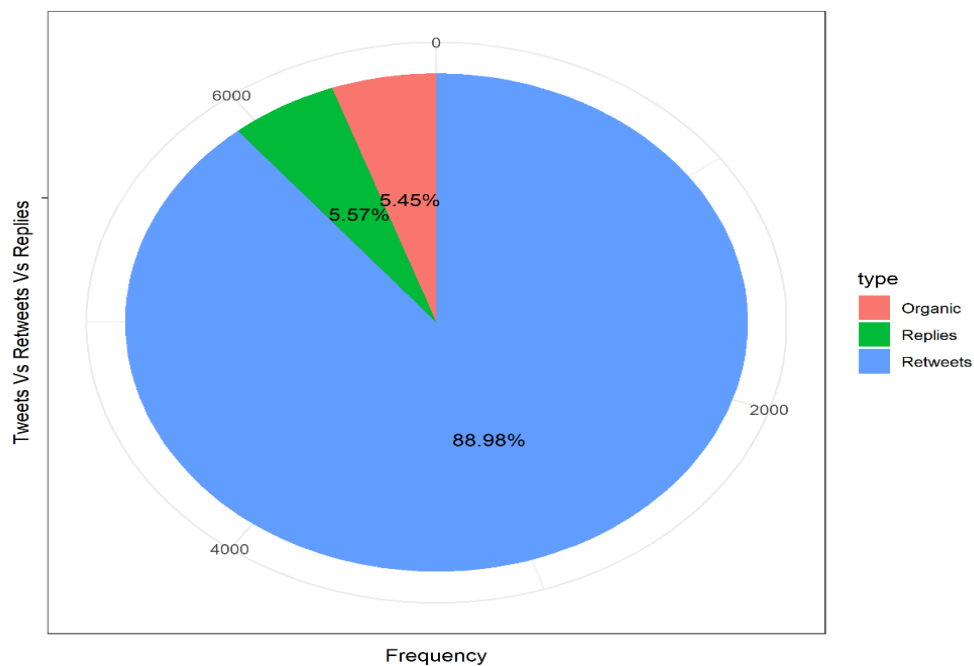
Figure 3. Description of the dataset

Instrumentation

As mentioned previously, the posting behavior of netizens on Twitter is based on specific features that are publicly available to users and detailed successively.

Response Variable (Dependent Variable): The first principal component was chosen to anticipate how people will comment on sanctions imposed on Russia during the Russian-Ukraine Conflict based on the information received by the users from diversified sources and publicly available user profile attributes. The netizen's posting behavior is influenced by nine attributes existing in the Twitter ecosystem (as discussed below) apart from the pre-established disposition of the users.

Predictor Variable: The study intends to investigate the contributing attributes that lead to the formation of polarization or de-polarization of attitudes that affects the posting behavior of the users on Twitter. We have chosen nine characteristics that reflect the essential elements of attitude formation on Twitter (see Table 1).

Table 1. Characteristics of attitude formation on Twitter

#	Characteristic	Description
1	Numstatuses	The number of tweets a person has made about a certain subject is represented by this variable. In other words, it counts how many unique tweets each user has posted. The number of tweets on a topic influences netizens' knowledge and, therefore, their attitude and tweeting behaviors.
2	Followers	Counts the number of a user's followers. "Follow" connections contribute to the development of a user's social network. When A follows B, the homepage of A will show B's tweets. The size of a social network's viewership is defined by its followers. As the number of followers increases, so do tweets' visibility and the rate of information transmission, as well as the likelihood of retweets and comments, which may influence tweeting behavior.
3	Friends	This variable represents the number of persons a user is following. People who follow a range of Twitter users are exposed to several perspectives on a certain topic, which may assist them in forming their own opinions. This richness of information could impact the user's tweeting behavior.
4	Favorites	This variable indicates the number of subjects or themes that a user regarded the most intriguing. The Favorite status notifies the original

		Twitter user that his or her tweet was liked. Users may also mark a tweet as a favorite and refer to it when sending a new tweet.
5	verifiedTRUE	This variable indicates whether an account is both genuine and of public interest. An account verified by Twitter may be used as a metric of tweeting behavior since the information transmitted via a verified account is deemed to be more trustworthy.
6	Numlists	This variable represents the number of groups to which a certain user belongs. A categorized collection of Twitter users is known as a "list." Users can create their own lists or cooperate with others while making a list. When a user reads a list's timeline, they are presented with a stream of tweets from the list's members as well as other members of the same community. The discourse occurring within a given group may impact the user's tweeting behavior.
7	numTopicTweets	This variable represents the number of topics a user follows. A user's profile menu may recommend topics to follow on the home timeline and in search results. Follow a topic to receive tweets, activities, and ads related to it. Additional subjects may be associated with a tweet based on a user's profile and behavior, such as the number of views or likes. More subjects a person subscribes to, the more likely they are to see similar tweets.
8	Twitter years	Indicates the age of a user's account. We assumed that a user's attitude toward the information exchanged with individuals and organizations would remain constant over an extended period of exposure to the Twitter ecosystem and that the accumulation of knowledge on a subject would not influence a user's tweeting behavior.
9	Positivity	Based on the frequency of positive and negative terms in a tweet, a positivity score is given. According to a tweet's sentiment polarity, its positiveness may be used as an indicator of tweeting behavior.

Pre-processing of data: When posting on Twitter, users include different non-textual items in addition to textual content, which must be removed before algorithmic review. In this instance, non-textual components of the tweets with no significant meaning or outside the scope of the current study were removed, including non-American Standard Code for Information Interchange (ASCII) characters, emoticons, mentions, digits, URLs, stop words, punctuation, and unnecessary spaces. Thus, the sanitized and processed information was accessible for further sentiment analysis and predictive modeling.

Algorithmic evaluation: By using the lexicon-based technique and the machine learning-based methodology, sentiment analysis may be performed on processed tweets. The research used the NRC Word-Emotion Association Lexicon to classify tweets into three semantic polarities

(positive, negative, and neutral) and eight emotion classifications (i.e., trust, surprise, sadness, joy, fear, disgust, anticipation, and anger). The study used principal component analysis to identify relevant tweets (PCA). PCA is a dimensionality reduction technique that transforms a large number of variables into smaller subsets that are representative of the information in the overall dataset (Abdi and Williams, 2010; Ringnér, 2008). Based on the similarities between the observations, it extracts the relevant data from the dataset and aggregates it into several documents known as principal components. Together with the individual's publicly accessible profile information, the identified principal component was utilized to predict the posting behavior of a Twitter user.

Findings

Semantic analysis of tweets

The overall semantic inclination of the organic tweets posted about the sanctions imposed on Russia was generated using RStudio's Syuzhet package (Jockers, 2017). The tweets were classified into positive and negative semantic polarities and further subdivided into eight emotions- anger, anticipation, disgust, fear, joy, sadness, surprise, and trust (see Figure 4).
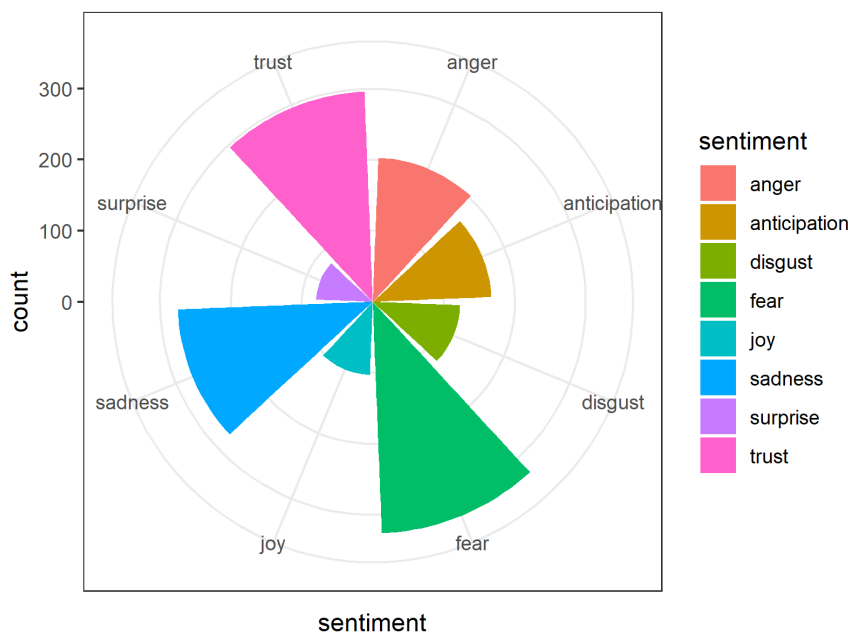
Figure 4. A semantic classification of tweets

Figure 4 demonstrates that the emotion of fear is dominant in most of the tweets followed by trust and sadness. Tweets for the above eight classifications of sentiments can be broadly segmented as positive or negative tweets. Figure 5 provides the top ten positive and negative terms used to draft tweets contained in our dataset. It can be deduced that tweets containing the terms such as "continue", "peace", "save", "supply", and "united" had a high frequency of occurrence in the tweets having positive semantic polarity.
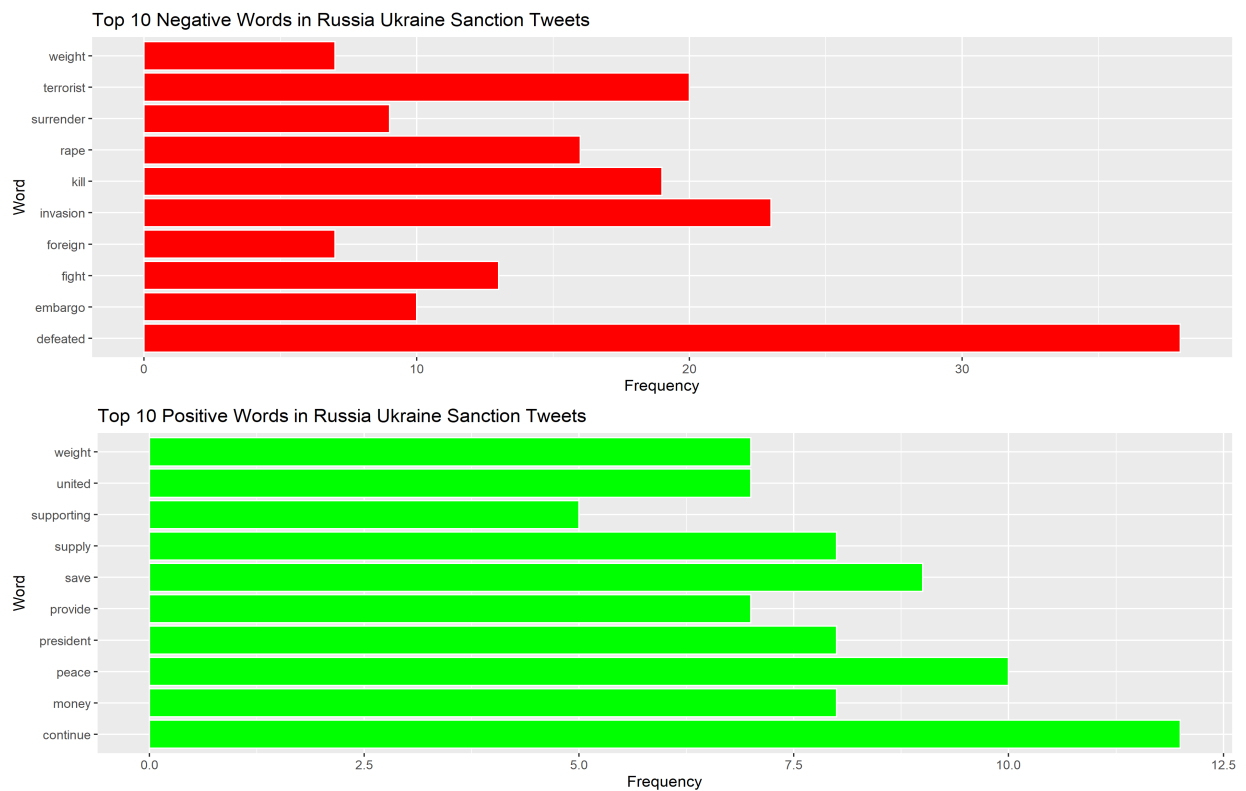
Figure 5: Top ten positive and negative terms

Tweets containing the terms such as "defeated", "invasion", "kill", "terrorist", and "rape" had a high frequency of occurrence and displayed a negative sentiment towards Russia Ukraine conflict (see Table 2).

Table 2: Tweets with negative semantic polarity

Tweets
This is why Ukraine can never surrender. Russia must be defeated in Ukraine; isolate them This is why Ukraine can never surrender. Russia must be defeated in Ukraine, isolate them and sanction their economy back to 1917. https://t.co/MG7wxI2wBs
Russia is terrorist! They kill people, rape children, and destroy cities. We ask for more #sanction and heavy weapon for Ukraine. Mariupol need public attention. https://t.co/IetOfJT0kX
Hello President, if you refuse to sanction MOGE, the Terrorist Junta in Myanmar will continue to use this revenue to purchase more weapons from Russia, creating more misery and violence in both Myanmar & Ukraine. https://t.co/Tg8rP0dO5n
#Russia's invasion of #Ukraine catalyzed a massive U.S. & #NATO pressure campaign -- sanctions, weapons etc. Good. For years in #Syria, #Russia bombed hospitals, IDP camps & schools; besieged 100,000s; covered for CW use & more. The response? Nothing. Not even x1 sanction. https://t.co/Iy1cpKUUZ4.
The G 7 pledge to ban or phase out the import of Russian oil in response to Russia's invasion of Ukraine. That's fine if they choose not to buy Russian oil, but it's not fine to threaten other countries, sanction ship insurers & even threatens ship seizures. https://t.co/IXHuZZcBQ5
Many thought #Hungary would quickly emerge as the "weak link" within the #EU in responding to #Russia's invasion of #Ukraine. And they are not. With each passing day, #Putin feels the loss of support somewhere in the world. https://t.co/Fct9LtQ82C
Russia handed further sanction by UEFA amid Ukraine invasion https://t.co/LDsbeHR159
Stop spreading propaganda. Ukraine has been killing its citizens and Biden knew it but he didn't sanction Ukraine. American has been pressuring Ukraine not to implement the minsk agreement. The western countries are spreading lies against Ukraine so as to weaken Russia. https://t.co/4qvF8QP48q
"Since Russia's invasion of Ukraine began several weeks ago, in-house legal leaders in many industries have had to navigate the complex and dynamic sanctions environment under unprecedented pressure," said Medtronic GC Ivan Fong. https://t.co/gQcXYsU4cE
Gas is highly needed now, followed by the Europe's sanction on Russia by reason of her invasion in Ukraine. But with the insecurity in Nigeria, many countries are afraid to approach us for Gas. Let's Restructure, or separate peacefully and go our separate ways competitively. https://t.co/X5C1C2nx9y

A sample of tweets containing these terms and positive semantic polarity is shown in Table 3.

Table 3: Tweets with positive semantic polarity

Tweets
I am proud to wear the Russian sanction as a badge of honor and will continue to voice my support for the Ukrainian people. https://t.co/oNMiXoxN0C
All the numbers are pointing to a crippling of the Russian economy & therefore their ability to continue the slaughter in Ukraine. But that's contingent on Western energy companies failing in their sanction busting effort which they would certainly try. https://t.co/m65r1gs5oG
No peace tslk or compromise with Ukraine unless all sanction should be revoked against Russia. https://t.co/ZJRmCmXwjd
For today's March for Ukraine we have clear messages: Support Ukraine with needed aid! Save Mariupol Garnison! Sanction Russia! https://t.co/MHr4pkaYYY
Indian Oil companies will buy stakes in Russian oil to consolidate energy supply https://t.co/Iu371g8pgY
Ukraine is still getting 70% of its oil supply from Belarus and Russia, that is against the sanction in place. Can the UK n Norway fix this? https://t.co/Xgyy6xB5qB
"#Oil market dynamics, where #diesel fuel is already in short supply and prices have risen to record highs, may make it very difficult to sanction products refined from Russian crude outside of #Russia." #sanctions #compliance #Ukraine https://t.co/l0uY8ENwgV
A carmaker from #Russia as asked #Iran to supply it with key components it can't access due to Western sanctions over #Ukraine invasion. https://t.co/rJhbFad9Cq
Hungary sends tons and tons of humanitarian aid. Money. Food etc. Supported every sanction EU made on Russia. Except oil. Accepts and handles and cares refugees from Ukraine. Hundreds of thousands. Sends weapons to Ukraine together with EU (not by its own). so? What else you need? https://t.co/U5ajsy67V9
Donating money to Ukrainian army and humanitarian need, demanding from your government to sanction Russia and/or arm Ukraine, even simple moral support is all important. You can help in so many ways, or you can bitch about "viRTue siGnAling", the choice is yours. https://t.co/M1m7NB35z8

Sentiment analysis showed the overall sentiment of Twitter users and the words used to communicate emotions on Twitter. Individuals' posting behavior on social networking sites is influenced by several factors. The research aggregated words based on semantic loading and sorted them into phrases using principal component analysis for predictive modeling.

Principal component analysis

Sentiment analysis breaks statements into words and compares them to preset keywords with polarity and emotion labels which enables individuals, groups, and organizations to automatically monitor and analyze social media content (Zhao, 2021). Each term's emotional

polarity and frequency in the bag of words determine its weight. These weighted words are the principal components according to topic modeling, i.e., frequent phrases are aggregated into a principal component. The initial terms in the first five principal components and the overall standard deviation of PC values of all principal components are shown in Table 4.

Table 4. Initial terms in the first five principal components

Term	PC1	Term	PC2	Term	PC3	Term	PC4	Term	PC5
alleged	0.12	rape	0.15	behind	0.15	happened	0.15	hopes	0.10
girlfriend	0.11	kill	0.14	thrown	0.15	fight	0.15	defeated	0.09
likely	0.11	destroy	0.14	weight	0.15	afghanistan	0.15	taiwan	0.09
vladimir	0.11	terrorist	0.13	demands	0.14	help	0.12	isolate	0.09
putines	0.09	children	0.13	parts	0.14	save	0.10	beijing	0.08
russiaukraine	0.08	citieswe	0.11	imports	0.12	west	0.09	must	0.07
alinacakabaeva	0.08	people	0.08	germany	0.04	defeated	0.02	sanctioning	0.07
union	0.08	moreea	0.04	alleged	0.01	isolate	0.02	inea	0.07
european	0.07	anea	0.01	likely	0.01	must	0.02	back	0.06
alina	0.03	eucommission	0.01	girlfriend	0.01	game	0.02	economy	0.06
Overall_SD	**2.61**		**2.48**		**2.41**		**2.19**		**2.14**

Since all the principal components are reflecting the core theme of this research i.e., sanctions imposed on Russia due to Russia Ukraine Conflict, and hence the selection of a principal component has been done by calculating the standard deviation of each principal component. With the intent to cover a broader view of the netizens, the study selects the first principal component that has the highest standard deviation value. A sample view of the tweeting trend based on the axial location in the first principal component has been shown in Table 5.

Table 5. Tweets in PCA 1 based on axial location

PC_Value	Tweet
(-1.46, -1.11]	This is why Ukraine can never surrender. Russia must be defeated in Ukraine, isolate them and sanction their economy back to 1917. https://t.co/FG7W27WDvP
(-1.11, -0.763]	Taiwan says hopes world would sanction China if it invades https://t.co/FoTu7SAJE7 #Ukraine #Russia #News

(-0.763, -0.419]	X: Do we need sanctions against China? Me: Why? X: Russia? Me: China trades with Russia and Ukraine, promotes negotiation. Most of the world trades with Russia ... are you planning to sanction India, Pakistan, Saudi Arabia etc? https://t.co/x8qFXWJvKz
(-0.419, -0.0747]	Russia is terrorist! They kill people, rape children and destroy cities.we ask for more #sanction and heavy weapon for Ukraine. Mariupol need public attention. https://t.co/T453sG6HsY
(-0.0747,0.27]	#Japan's economy, trade and industry, minister #KoichiHagiuda showed a negative view about keeping pace with the #EU over its plan to ban oil imports from #Russia as an additional sanction against #Moscow following its invasion of #Ukraine #giappone #notinmyname #fukushima. https://t.co/jwCybHNLjf
(0.27,0.614]	Sanction demands and sanction can come later right now Ukraine need humanitarian aid for civilians. Russia has almost fullfill it's agenda after winning the war and breaking Ukraine . Now is the time to help civilian and restore parts of Ukraine. https://t.co/cxvPYsytyL
(0.614,0.958]	As EU ambassadors to meet to thrash out sanctions package, Hungary's Orban describes the proposed sanctions as a "nuclear bomb" for Hungarian economy. Wants 5-year delay for phase out (currently Slovakia + Hungary offered an extra yr). https://t.co/5abGpxfyQB
(0.958,1.3]	The EU has proposed sanctioning Alina Kabaeva, a former gymnast reportedly closely associated with Vladimir Putin, according to a document seen by Bloomberg https://t.co/ybDwzkKrnT
(1.3,1.65]	Russia-Ukraine war live updates: At least 60 feared dead after Russian airstrike on school. Sanction everything and everyone associated with Russia. https://t.co/bAWZLquM1s
(1.65,1.99]	What exactly is the end-game with Russia-Ukraine?? How much can USA afford?? & at what cost?? The USA should get out of this 'Democracy' & 'Sanction' whatever we don't like game. Give "Capitalism" a fighting chance to survive https://t.co/gSlt1zQwE9
(1.99,2.34]	EU targets Putin's oil, banks and propaganda in new sanctions plan. https://t.co/Z2GSkyE6v2
(2.34,2.68]	"European Union diplomats say the EU plans to sanction the head of the Russian Orthodox Church in its next round of measures to punish Russia's invasion of Ukraine." https://t.co/TfhAHuQ1CA
(2.68,3.02]	Japan's industry minister showed a negative view Wednesday about keeping pace with the European Union over its plan to ban oil imports from Russia as an additional sanction against Moscow following its invasion of Ukraine. https://t.co/XyIEm3l6gp
(3.02,3.37]	Japan's industry minister has shown a negative view about keeping pace with the European Union over its plan to ban oil imports from Russia as an additional sanction against Moscow following its invasion of Ukraine. https://t.co/0eSJ8pM2bQ
(3.71,4.06]	The European Union proposed a phased-in embargo on Russian oil imports, the delisting of more Russian banks from the Swift payment messaging system and fresh sanctions targeted at people spreading disinformation on Russia's war in Ukraine. https://t.co/itDyAEXFDN
(4.06,4.4]	The European Union has proposed a new package of sanctions over Russia's war in Ukraine, EU officials said, including a phased-in embargo on Russian oil imports https://t.co/TCQvWjFpSp
(5.09,5.44]	EU to sanction Vladimir Putin's gymnast lover Alina Kabaeva. https://t.co/awpvp2GnnC

It can be observed from Table 5 that the posts on various sanction initiatives are more general on the lower co-axial location of the PCA1. As the PC values move towards positivity, the posts become more centric towards the sanctions imposed by the European Union on the Russian oil trade. The translation of PC values and tweeting behavior is dependent on the user's pre-established attitude in conjunction with the user's public profile attributes available on Twitter. The degree of influence that an attribute has over the tweeting behavior of a user has been further investigated through predictive modeling in the next section.

Predictive modeling

Multivariate Shapiro–Wilk tests were performed using the R program's myShapiroTest function (Gonzalez-Estrada and Villasenor- Alva, 2015). Analysis indicates that data were not normal and hence the Ordinary Least Square approach could not be employed for predictive modeling. Hence the study uses a generalized linear model (GLM) for establishing the relationship between the response and predictor variables. The generalized linear model (GLM) is a versatile extension of traditional linear regression (McCullagh and Nelder, 2019). For each measurement, the variance is tied to the predicted value through a link function, which is possible with the GLM since it allows the linear model to be linked to the response variable (McCullagh and Nelder, 2019; Turner, 2008). Table 6 shows the analysis result of the generalized linear model.

Table 6. Regression using the generalized linear model

Call: glm (formula = PC1~ numstatuses + followers+ friends + favorites + verifiedTRUE + numlists + twitter_years + numTopicTweets + positivity, family = "gaussian", data = cybersecurity, subset = trainset)				
Deviance Residuals: Min	1Q	Median	3Q	Max
-1.2847	-0.275	-0.1386	-0.0172	5.8284
	Estimate	Std. Error	t value	Pr(>|t|)
Coefficients				
(Intercept)	-3.11E-01	8.12E-02	-3.832	0.000***
numstatuses	-1.21E-07	2.94E-07	-0.413	0.680
followers	-2.17E-08	5.63E-08	-0.386	0.700
friends	7.98E-06	5.67E-06	1.409	0.160

favorites	-5.85E-07	7.95E-07	-0.736	0.462
verifiedTRUE	-2.18E-01	1.60E-01	-1.364	0.173
numlists	3.78E-05	1.11E-05	3.401	0.000***
twitter_years	1.17E-02	8.84E-03	1.322	0.187
numTopicTweets	-2.16E-02	4.21E-02	-0.514	0.607
positivity	-3.70E-02	3.41E-02	-1.04	0.279

The dispersion parameter for the Gaussian family is taken to be 0.6450397
Null deviance: 302.29 on 443 degrees of freedom
Residual deviance: 279.95 on 434 degrees of freedom
Akaike information criterion (AIC): 1077.2
Number of Fisher Scoring iterations: 2

Table 6 shows that the model's median deviation is so close to zero, that it can be concluded that the model is impartial and does not over- or under-estimate the findings. The training model's appropriateness was also determined by lower residual deviance values (279.95 on 434 degrees of freedom) with a loss of nine degrees of freedom as compared to null deviance (302.29 on 443 degrees of freedom) and a lower Akaike Information Criterion (AIC) value (Yadav, Misra and Singh, 2022; Yadav, Misra, Rana and Singh, 2022; Yadav, Misra, Rana, Singh, *et al.*, 2022). The pre-existing attitude was found to be negatively polarized (β = -3.11E-01, SE = 8.12E-02, p<0.001). Only one variable i.e., Numlists was found to be a significant contributor in modulating in pre-existing behavior of the users (β = 3.78E-05, SE = 1.11E-05, p<0.001).

Propositions and conceptual framework

In this section, we provide three propositions based on the empirical analysis of the data. The propositions illustrate the possibility of seeing how varied media and information interchange may have a significant impact on individuals.

Proposition 1: The real-life and virtual-world experiences of participants and the extent to which they are exposed to social media, contributes to the diverse expectations put on information providers and influence the partisan and bipartisan perspectives.

Individuals, professionals, and organizations may use their offline experiences as a basis for modeling their online and social media cognitive behavior (Kizgin *et al.*, 2020; Modgil *et al.*,

2021). Users' worldviews are shaped by their expectations and their online experiences. It is unusual for social media users to get information on a topic they're interested in or one they're following without scrutinizing the source (Duffy *et al.*, 2020; Modgil *et al.*, 2021). As social media postings are created by a diverse array of individuals, groups, and organizations, it is increasingly difficult determining what information is authentic and fake (Dong *et al.*, 2019). Essentially, social media exposure and expectations, which cover both online and offline experiences, influence public attitudes and behavior (Banerjee *et al.*, 2021; Cocosila and Igonor, 2015).

Proposition 2: Users' behaviors drive algorithmic personalization, which leads to filter bubbles, and vice versa. These filter bubbles influence the biases of individuals, communities, and institutions, as well as contribute to the construction of echo chambers.

Filter bubbles occur when like-minded individuals are not exposed to contrary perspectives or opinions, which can lead to tunnel vision and enable confirmation bias (Xu *et al.*, 2020). However, with the advent of new web-based media, numerous processes have been introduced that allow websites to collect significantly more particular information. Buttons like "share", "like", "subscribe", and so on help algorithms learn more about netizens' online activity. The tendency toward personalization of online material is harmful to social media users because users are no longer exposed to content that may broaden their interests or question their views, opinions, or beliefs (Pariser, 2011). In other words, social network users are increasingly unable to escape the "filter bubble" that isolates them from various points of view and dampens their natural curiosity. Many users' online social circles are primarily made up of people who share their interests and opinions. Therefore, people create online communities in which they trade and receive information relevant to their interests and consistent with their worldview. Not only does this lead to echo chambers', but its impact includes excluding alternative perspectives (Gillespie *et al.*, 2014) and political chaos in many contexts (Kim and Kim, 2019).

Proposition 3: Influencers contribute to the establishment and growth of new knowledge and information bodies that contribute to the presentation of social identity. The behavior of publishing content on a range of digital platforms is analyzed to determine an individual's preferences for certain categories of personalized content.

Instead of being well-known for their professional skills, as traditional superstars do, social media influencers have become well-known for their expertise (in a certain topic) on social media. Influencers in the business are content creators that create and disseminate credible knowledge on a certain topic (Aw *et al.*, 2022; Belanche *et al.*, 2021). Because of the difficulties that marketers have in effectively engaging consumers in virtual communities, these influencers are becoming more crucial to brands (Kapitan and Silvera, 2016). The fundamental difference between conventional celebrities and influencers is that influencers are viewed as fellow customers, while traditional celebrities are not (Kim and Kim, 2021). Connecting with an influencer is possible when they exhibit a friendly personality (i.e., genuineness), demonstrate that the influencer and supporters face similar problems in their lives (i.e., visibility), and make genuine product recommendations (Godwin, 2018; O'Leary, 2021). Consequently, the connections between influencers and their followers, which provide a more in-depth glimpse into the influencer's lifestyle and hobbies than traditional superstars can, are projected to raise the significance of congruence and realign netizens' current behavior. Several recent research on social media-based behavior analytics has recently validated the use of influencers as attitude-change agents (Yadav *et al.*, 2023; Yadav, Misra, Rana and Singh, 2022).

Based on the emergent theme of echo chambers and the role of influencers in digital social communications, a conceptual framework for social media-induced de-polarization is illustrated in Figure 6.
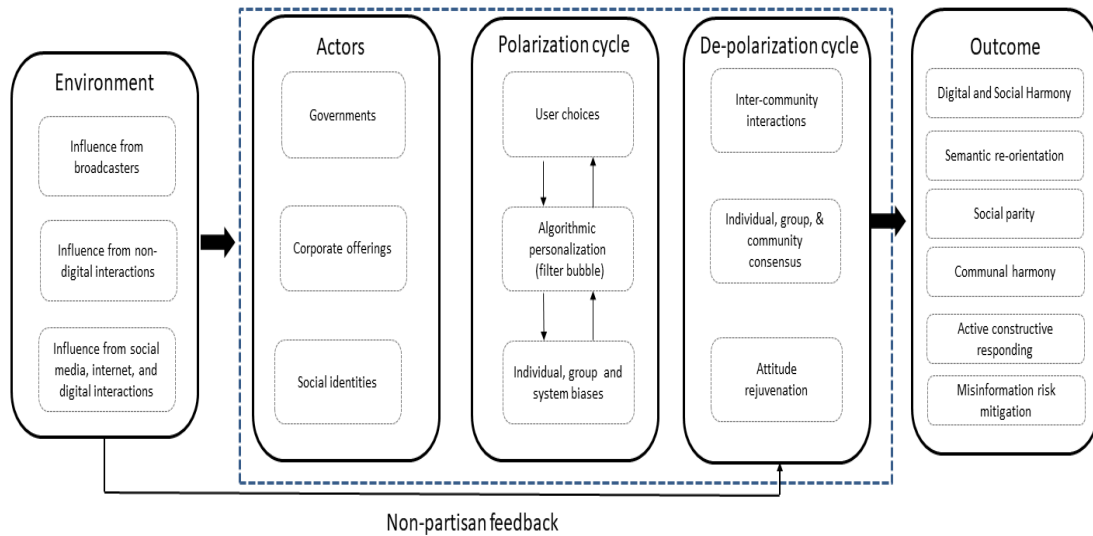
Figure 6. Conceptual framework for social media induced depolarization

Discussion

Social media platforms that offer a platform for unmediated and unverified open communication among people often result in the establishment of polarized viewpoints (Zhen *et al.*, 2022). The notion of attitude polarization is derived from the theory of echo chambers, in which a person purposefully or unintentionally consumes a string of information that corresponds with their current disposition and psychology (Modgil *et al.*, 2021). This research examines the posting behavior of Twitter users to investigate the underlying notion present in echo chamber theory. The first sentiment analysis of all the tweets retrieved for this research shows that fear is the most common feeling among netizens, followed by trust and sadness. There is preponderance of negatively polarized tweets, whereby netizens have criticized Russia's non-humanitarian activities. On the other hand, in their tweets, netizens have utilized positively polarized terms to convey their support for the numerous sections imposed over Russia to discourage the continuing invasion of Ukraine. Though the initial semantic inclination of all tweets revealed the emotions dominating the overall tweets, it fails to explain the prevalent elements contributing to attitude building when conversations take place through social media. An assumption of this study is that publicly accessible users' profile information

and tweets created by other users, might have substantial potential in modifying a netizen's tweeting behavior. The predictive modeling findings reveal that pre-existing attitudes and external learnings (i.e., outside of the Twitter ecosystem) have a detrimental impact on netizens' tweeting behavior. This behavioral tendency of netizens may be attributed to the partisan segregation of information from non-digital encounters, blogs, news media, and other online sources, which can operate as echo chambers and further polarize a person's mindset (Alyukov, 2022; Garrett, 2009; Koltsova and Pashakhin, 2020). This polarized behavior may be depolarized and realigned by consuming information provided by netizens in a specific social media environment (such as Twitter). Table 5 illustrates that the number of groups to which a user belongs (as shown by the variable 'numlists') has a favorable impact on their tweeting behavior in the Twitter environment. A user is linked to a bigger community with diverse semantic orientations and logical inferences about a phenomenon by belonging to distinct groups. These intergroup contacts promote conversation and consensus while also aiding in the depolarization of attitudes (Hinck and Carr, 2021; Imperato *et al.*, 2021; Wong *et al.*, 2022).

Implications for research

Since the conflict between Russia and Ukraine began, a number of studies have been conducted to examine the communications taking place between nations, governments, businesses, and individuals via electronic media (Gavra and Savitskaya, 2011; Golovchenko, 2022; Makhortykh and Bastian, 2022; Makhortykh and Sydorova, 2017; Nedozhogina, 2019). Political ideology, conflict management, media-induced behavior, and e-governance have all been studied using communication and media studies. While research in the field of communications studies provides insights into how government agencies and organizations adjust communication to maintain their social identity as well as manage the general public's thinking process and behavioral disposition in times of crisis, the majority of these findings are based on traditional methods such as interviews, discussion, and opinions (Gavra and

Savitskaya, 2011; Hauter, 2021; Whitley *et al.*, 2014). Because individuals are more willing to share information about themselves and their interests with the rest of the world, social media analytics may give more thorough information about people's moods (Reychav *et al.*, 2019).

By extracting users' emotions from their social media postings using non-traditional research approaches this study advances knowledge of social media analytics. Specifically, the research extends beyond the original analysis of the user's emotional predisposition as portrayed in their social media posts to establish an empirical link between the user's attitude construction and the social media user's profile attributes. It is also the first research on the Russia-Ukraine conflict to use social media analytics and to propose a method for depolarizing opinions. The study also contributes to the understanding of echo chambers by illustrating that the user's behavior of consuming polarized information with a self-serving bias may be disrupted by the intervention of information supplied by various sources in diverse social media communities.

The findings suggest that social media platforms (e.g., Twitter) might act as behavior de-polarizers in times of crisis, facilitating societal and business harmony. The research reveals the characteristics and empirical evidence of the evolution of attitudes toward crisis management on digital social platforms.

Implications for practice

People often embrace conflicting points of view during times of crisis, and in some cases, these contrasting points of view are the consequence of inadequate or erroneous information distributed by several sources. This study discovered that social media users had significantly polarized behavior, but a further in-depth analysis discovered that these users are open to conversation and want to have their opinions de-polarized. The study was carried out as part of an investigation into the most current situation between Russia and Ukraine. To be effective, however, attitude depolarization must begin with the development of information (or

communication) from a reliable source outside of the organization. A few recent studies on social media-based behavior analytics have lately supported the usage of nano-influencers as attitude-modification agents (Yadav *et al.*, 2022). In keeping with the suggestions provided by previous studies, we propose employing nano-influencers in local hotspots to restore harmony and combat any misleading information that may be spreading during this crisis.

Information given to the public by influencers has a significantly greater chance of being accepted due to their broad presence across a range of social media platforms and their high degree of social capital, not just in their local geographic region but also on a wider scale. Furthermore, since these influencers are concerned about their social capital and public acceptance, they avoid disseminating misinformation and may even take pleasure in correcting it. As a result, in times of crisis, organizations and governments should welcome people with significant social capital and a high engagement rate to promote authentic information and prevent disinformation from spreading.

Limitations and future research

As with all research, we acknowledge this study has limitations, which also offer directions for future research. First relates to Twitter's data structure as tweets can sometimes lack context or are too short to express genuine sentiment, and even be obscured by an image, emojis, or website link. People often construct acronyms on the spot or omit words whose existence may be deduced by humans while discussing specialized subjects. The most common option is to simply exclude them from the dataset; however, this excludes vital information and may skew the results. Given the message length restrictions on user postings (280 characters per post), future research could examine other social media platforms that have expanded posting limitations, enabling users to express themselves more effectively. Future research could develop methods for merging emojis and visual data in order to better analyze changes in user attitudes over time within the social media ecosystem.

Secondly, the study is limited to the extraction of tweets posted in the English language and hence eliminates the conversations in non-English languages or regional languages. The primary reason for this selective mining is associated with the use of libraries used for the allocation of sentiment scores to the tweets. Future researchers could focus on the development of semantic libraries for various regional languages and replicate this study in various contexts with a broader population.

Thirdly, this study focused on organic tweets, while most tweets in a conversation are responses to previous tweets. Replies are a common feature of Twitter user engagement as they serve as the foundation for conversation and they reflect the directionality of the social media message, as well as the influential members of a digital community. Future research could use network analyses to assess the reach and effectiveness of a message in affecting user views about a specific topic or event. In doing so, future research could then identify users with high social capital and suggest techniques for their effective use in polarizing/depolarizing user behavior that could lead to a better-informed society.

Conclusions

The research delves into the delicate issue of the Russia-Ukraine conflict and uncovers netizens' emotional reactions to the different sanctions placed on Russia. The study discovered that netizens had a predominance of negative feelings, such as fear and sadness, over the lives of Ukrainians, but that the quotient of trust in the countries backing Ukraine was also strong. An in-depth examination of social media data shows that netizens had a pre-established polarized attitude toward this crisis scenario. However, this polarized behavior may be de-polarized by efficient communication across the different groups on social media and information provided through reputable sources. The study recommends that governments and businesses use nano-influencers to counteract misinformation and promote social harmony. In

addition, techniques like bigrams, n-grams, and social network analysis may be utilized to examine the patterns and word associations in the posts. We hope that organizations and nano-influencers will be able to use these findings in their social media postings to avoid causing additional trauma for those affected by conflict.

Disclosure statement

The authors declare that they have no conflict of interest.

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