# Ukrainian Thoughts and Feelings Based on One Year War Content Analysis

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**Abstract:** In the age of remarkable technological innovations such as AI, quantum computing, IoT, and blockchain, one could argue that the world is becoming an increasingly connected, advanced, enlightened, and peaceful place. Nevertheless, paradoxically, conflicts and wars are still born deeply rooted in complex strategic, historical, and economic dynamics, and continue to arise finding a direct representation in both physical and digital battlefields through powerful and dynamic environments like social media. This environment enabled unprecedented connectivity and ideas, thoughts, ideologies, and experiences exchange shaping the narrative, amplifying ideas, feelings, and experiences while directly addressing the underlying causes, dynamics, and implications of conflicts and war through a multifaceted and multi-nuanced approach. The outbreak and ongoing war in Ukraine took the international community off guard representing a significant turning point in the contemporary era that received immediately intensive global attention, united global humanitarian, and strategic efforts to support and help the ones in need, and reflected its geopolitical and economic global complexities, dynamics, and implications. At the same time, a high degree of disinformation and misinformation exists surrounding different aspects about this war e.g., actions taken, and impact produced on civilians, which contributes to creating an altered perspective of reality. While different conventional media and social media outlets together with research, governmental, and practitioner efforts revealed and reflected on the nature, major incidents, and their known impact on civilians and civilian objects as well as military personnel and military objects, yet limited attention and a lower voice is given through dedicated studies to thoughts and emotions of Ukrainian users in unconventional social media platforms like Telegram. This represents the knowledge gap tackled in this research by building a set of Machine Learning-based solutions for analysing the discourses and sentiments of Ukrainian users using the Design Science Research methodology in a Data Science research approach. From this analysis, reflection is provided to important days and incidents experienced by Ukrainian population since February 2022 in the first year of war.

**Keywords**: Ukraine war, Russia-Ukraine war, Topic modelling, Sentiment analysis, Machine learning

## 1. Introduction

*"Before a war military science seems a real science, like astronomy; but after a war it seems more like astrology." (Rebecca West)*

The ongoing war in Ukraine continues to send shockwaves through the global conscience and profound political, ideological, social, and economic consequences are reverberated far beyond the battlefield, forcing nations to rethink their alliances, strategies, policies, and programs. In this digital age, this war represents a tumultuous transformation where social media platforms together with their discourses, experiences, and emotions serve as both catalyst and chronicler. Yet, through viral posts and real-time content, social media manipulation mechanisms like disinformation and misinformation are intertwined in a tumultuous dance by spreading next to real also altered war insights, perspectives, struggles, and opinions (Fard & Maathuis, 2021; Agarwal, Punn & Sonbhadra, 2022; Sedrakyan, 2022). Hence, the urgency of safeguarding cyberspace by illustrating real aspects characterizing discourses, experiences, and feelings of Ukrainian people directly involved in this conflict are critical for discerning truth from falsehood and for understanding the impact of these battles beyond the physical battlefield (Alibudbud, 2022; Maschmeyer et al., 2023). During this war, Telegram represents the unconventional social media platform that most quickly rose in popularity and use due to its various channels (Nazaruk, 2022) and its power to provide the latest information about various war aspects (Ptaszek, Yuskiv & Khomych, 2023). However, while dedicated efforts to understanding discourses and emotions of users in other social media platforms like Twitter exist, a limited body of studies is directed to unconventional social media platforms like Telegram and TikTok (Zhu et al., 2022). This creates a gap in understanding these through such platforms (Steel, Parker & Ruths, 2023) and without tackling them, the spread of social media manipulation increases (Ye et al., 2023).

Hence, the aim of this research is to capture essential topics tackled in Ukrainian discourses together with corresponding sentiments in Telegram in the first year of war, between February 24, 2022, to February 23, 2023, and through this approach to contribute to reducing or countering ongoing social media manipulation campaigns that focus on spreading disinformation and misinformation about this war. Accordingly, the main research question formulated is: What are the main discourses and corresponding sentiments of Ukrainian Telegram users in the first year of war? Building on previous efforts in a transdisciplinary context, the Design Science Research Methodology is followed in a Data Science approach (Shearer, 2000; Peffers et al., 2007). Accordingly, the contributions of this research are defined as follows:

- A series of Machine Learning models for extraction and analysis of topics and sentiments based on a Telegram dataset with Ukrainian messages from the first year of war.
- A basis for enhancing social media manipulation countering efforts against disinformation and misinformation on platforms that receive less research attention like Telegram, representing a call for further joint research and practitioner efforts on this behalf.

The remainder of this article is structured as follows. Section 2 discusses the background and important relevant studies regarding related datasets and methods built for understanding diverse dimensions that characterise the discourses and dynamics of the ongoing war in Ukraine. Section 3 presents the methodological approach as well as the implementation choices taken in this research. Section 4 shows the results obtained tackling both topics discussed and corresponding sentiments of users. Conclusively, Section 5 provides concluding remarks and future research perspectives.

## 2. Related Research

Sedrakyan (2022) analyse the implications of sanctions applied to Russia between 2014-2018 as a response to political instability in Ukraine, annexation of Crimea, human rights violation in Russia, and interference in the US 2016 presidential elections. The dataset contains sanctions applied by Western and US countries in relation to their impact on transition economies. Alibudbud (2022) investigates trauma-related aspects regarding PTSD (Post-Traumatic Stress Disorder) of Ukrainian people based on Google trends. While the authors are focusing on data between January to March 2022 and include main conflict areas at that time, the results show an increase by almost 50% in PTST-related searches and show that humanitarian efforts need to include PTSD-related services and that substantial public concern should also be directed to PTSD screening and services. At the same time, Khalfaoui, Gozgor & Goodell (2023) stress the dependency between cryptocurrencies and investment horizon and market state, and further examine the impact (negative or positive) of the war in Ukraine on cryptocurrencies like Bitcoin and Ethereum between February 24 to June 21, 2022. The results obtained show a negative impact in most cases and point out that decision makers should be more concerned by the asymmetric connectedness between markets. While not related, yet in the same area of economic implications, Wiertz, Kuhn & Mattissek (2023) analyze one year of Twitter, newspapers, and political talks discourses regarding energy transition between February 24, 2021 – February 24, 2022. The study reports the following four discursive shifts caused by geopolitical turn: controversies regarding gas import, new moral imperative to reduce dependence on Russian gas, increase in popularity of resources like nuclear power, accelerated implementation through funding for renewable energy solutions.

Kravchenko (2022) investigates anti-Ukrainian discourses of Russian politicians with a high degree of granularity focusing on topics like the liberation of Ukraine, the Villian role, the hero-liberator construction, and the we-they dichotomy. Furthermore, Hanley, Kumar & Durumeric (2023) conduct a comprehensive discourse analysis on Western, Russian, and Chinese discourses carried out between January 01 up to April 15, 2022. The analysis focuses on three news ecosystems: Bucha, Mariupol, and general events. Accordingly, the study mentions the difference in perspective between the three types of discourses. While on the Western side the focus is more on military aspects and destruction (e.g., *dead, killed, bodies*), the Russian side has the focus on Donbas region and the portrayal of the Ukrainian government (e.g., *repel Kiev's aggression, liberate the regions*), the Chinese side focuses on its concerns regarding economic and diplomatic fallout of the war in Ukraine (e.g., e.g., *negotiations*). Agarwal, Punn & Sonbhadra (2022) analyze public discourses and their dynamics on Twitter using the Kaggle Russia-Ukraine war dataset, with data between December 31, 2021, to March 03, 2022. Moreover, the study depicts the word cloud representation, a summary of tweets and likes, and the frequency of positive, negative, and neutral tweets. Among the topics mentioned are *standwithukrinae, Ukraine border, troops, border, Russia, NATO, Ukraine crisis,* and *people.* Moreover, Haq et al. (2022) build a Twitter dataset between the start of the war until March 06, 2022. The dataset contains 1.6 million tweets, and among the topics with the highest frequency found are *breaking, news, exclude, amid,* and *suspends*. Shevtsov et al. (2022) provide a Twitter dataset from the beginning of the war up to April 07, 2022, containing 57.3 million tweets. The study mention English, French, German, Spanish, and Italian among the most popular languages of the tweets collected. Hakimov & Cheema (2023) advance a Twitter dataset with approximately 1.5 million tweets in 60 different languages with tweets between February 01, 2022, to May 31,

2023. The top languages rated are English, Arabic, Spanish, French, and German. Moreover, a general negative sentiment can be seen with slight improvements in moments of time such as the Independence Day in August 2022 and the visit of Biden in Kyiv in March 2023. Although on a different platform, these results are aligned with the results obtained in our article.

In particular, Caprolu, Sadighian & Di Petro (2022) conduct a Twitter aspect-based sentiment analysis between January 27 up to March 23, 2022, focusing on five types of accounts: baby, trusted, abnormal, unknown, and regular. The study reveals that celebrities and popular accounts were from the beginning active in posting and engaging in different discourses related to this topic. Furthermore, Chen & Ferrara (2023) propose a Twitter dataset between February 22, 2022, to January 08, 2023, and analyze both the discourses and relations between the users engaged. The top five languages are English, Spanish, French, German, and Italian, and among the correspondences between country of users can be mentioned US -> US, Ukraine -> US, US -> Japan, for the pair quoted country -> quoter country. For tackling different social media manipulation, Toraman et al. (2022) analyze misinformation tweets in English and Turkish for building a deep learning-based misinformation detection on Russia-Ukraine war, Covid-19, and refuges. The data collected in English is between September 10, 2020, to March 21, 2022, and the data collected in Turkish is between October 5, 2020, to March 11, 2022. Using a similar approach, Thapa et al. (2022) build a multi-modal Twitter dataset (i.e., both text and image data) with data from February 22 to March 28, 2022. The authors build Generative AI models using techniques like RoBERTa and CLIP for content classification as being hate speech or not related, obtaining values of F1 score of 0.83 and 0.89, respectively. Similarly, Pierri et al. (2022) bring a Facebook and Twitter dataset of 250 million tweets with data ranging from February 01 to April 24, 2022, and propose a propagation and misinformation detection solution.

On other less classical platforms, Fung & Ji (2022) propose the Weibo dataset with 27.341 posts captured from the beginning of the war up to March, 08, 2022. The top five topics discussed are *Ukraine, Russia, Russia-Ukraine, Kiev,* and *Putin.* Park et al. (2022) build a dataset with more than Twitter and VKontacte 38 million messages between February 24 to July 31, 2022, from state-affiliated and independent media outlets. The authors frame the discourses tackled by both communities and position topics regarding *morality, fairness, legality,* and *crime* in the independent sphere, and topics regarding *capacity* and *external* in the state-affiliated sphere. Zhu et al. (2022) propose a Reddit dataset containing more than 300.000 posts between February 24 to May 29, 2022. The study classifies the content as being related to this conflict or general military related. The authors state that a general military post is more likely to receive more replies than the Russian-Ukraine conflict. On Tiktok, Steel, Parker & Ruths (2023) build a dataset around the war in Ukraine containing videos and comments from 2022. The top five languages identified are German, English, Indonesian, Russian, and Ukrainian, and the top five leader mentions are Putin, Zelensky, Biden, Trump, and Macron.

Hanley & Durumeric (2023) conduct an in-depth analysis on communication behavior and topic analysis of Russian media outlets and Telegram channels between January 01 to September 22, 2022. The authors stress that with time, during war, a decrease of using Western applications by Russian users was seen in parallel with an increase in using Telegram channels. Among the topics discussed are the possibility of achieving peace in Donbas in Telegram specific discourses, cessation of hostilities and political dialogue in Russian site specific discourses, and advancements of airborne units in shared Telegram and Russian site discourses. Nazaruk (2022) takes an archiving perspective by collecting 4 TB of Telegram data from around 1000 channels with communication between February 24 to July 31, 2022. The channels are grouped in categories like official and news channels, IT community/information and cyber-attacks, border crossings, Russian propaganda and fakes, medical and psychological assistance, and military mobilization. Ptaszek, Yuskiv & Khomych (2023) analyze Telegram communication between February 24 to June 03, 2022, on RIAN channel which is controlled by the Russian government and UNIAN which is the first and largest independent news agency from Ukraine. While the most used words on RIAN are *Russia, Ukraine, military, military of defence, Putin, DPR, USA, head, sanctions, foreign minister, troops, forces, Mariupol, operations, Zelensky, negotiations, residents,* and *city*, on UNIAN the most used words are *Ukraine, Russia, occupants, invasion, situation, solution, the border, armed forces, military, action, forces,* and *destroy.*

**Table 1: Related studies and proposed datasets**

| No | Objective | Dataset period | Source |
|---|---|---|---|
| 1 | Economic sanctions analysis | 2014 – 2018 | Sedrakyan (2022) |
| 2 | PTSD search analysis | January – March 2022 | Alibudbud (2022) |

| No | Objective | Dataset period | Source |
|---|---|---|---|
| 3 | Cryptocurrency impact analysis | February 24 – June 21, 2022 | Khalfaoui, Gozgor & Goodell (2023) |
| 4 | German energy discourses shift analysis | February 24, 2021 – February 24, 2022 | Wiertz, Kuhn & Mattissek (2023) |
| 5 | Anti-Ukrainian discourse analysis of Russian politicians | Not acknowledged, study published in 2022 | Kravchenko (2022) |
| 6 | Western, Russian, and Chinese media outlets discourse analysis | January 01 – April 15, 2022 | Hanley, Kumar & Durumeric (2023) |
| 7 | Public opinion analysis on Twitter | December 31, 2021 – March 03, 2022 | Agarwal, Punn & Sonbhadra (2022) |
| 8 | Twitter dataset | February 24 – March 06, 2022 | Haq et al. (2022) |
| 9 | Twitter dataset | February 24 – April 07, 2022 | Shevtsov et al. (2022) |
| 10 | Twitter dataset and sentiment analysis | January 27 – March 23, 2022 | Caprolu, Sadighian & Di Petro (2022) |
| 11 | Twitter English and Turkish dataset, war, and refuges misinformation detection | September 10, 2020 – March 21, 2022, for English, and October 5, 2020 – March 11, 2022, for Turkish | Toraman et al. (2022) |
| 12 | Twitter and VKontakte dataset, state-affiliated and independent discourse analysis | February 24 – July 31, 2022 | Park et al. (2022) |
| 13 | Twitter dataset | February 01, 2022 – May 31, 2023 | Hakimov & Cheema (2023) |
| 14 | Twitter dataset | February 22, 2022 – January 8, 2023 | Chen & Ferrara (2023) |
| 15 | Multi-modal Twitter dataset, hate speech detection | February 22 – March 28, 2022 | Thapa et al. (2022) |
| 16 | Facebook and Twitter dataset, propaganda, and misinformation detection | January 01 – April 24, 2022 | Pierri et al. (2022) |
| 17 | Weibo dataset | February 24 – March 08, 2022 | Fung & Ji (2022) |
| 18 | Reddit dataset and discourse analysis | February 24 – May 29, 2022 | Zhu et al. (2022) |
| 19 | TikTok dataset and discourse analysis | February 24 – December 31, 2022 | Steel, Parker & Ruths (2023) |
| 20 | Russian media outlets and Telegram behaviour and topic analysis | January 01 – September 22, 2022 | Hanley & Durumeric (2023) |
| 21 | Telegram dataset and archiving | February 24 – July 31, 2022 | Nazaruk (2022) |
| 22 | Telegram news agency discourse analysis | February 24 – June 03, 2022 | Ptaszek, Yuskiv & Khomych (2023) |

The extensive literature review conducted in this research and summarized din Table 1, reveals two important aspects regarding existing solutions built for understanding discourses, topics, and sentiments of users. First, illustrates the complex nature of this phenomenon and the diversity of aspects tackled. And second, shows that while most studies focus on traditional platforms like Twitter, there is a need for more research and AI-based solutions for understanding the same discourses, topics, and emotions also in non-conventional platforms like Telegram and TikTok. This represents the knowledge gap that this research tackles building on previous work in this domain for encouraging further efforts in this direction.

## 3. Research Approach and Implementation

This research aims to capture topics and corresponding sentiments in Telegram discourses of Ukrainian users building upon previous work (Maathuis & Kerkhof, 2023a; Maathuis & Kerkhof, 2023b) by developing a series of Machine Learning models in a transdisciplinary approach. Accordingly, the Design Science Research Methodology is followed in a Data Science approach (Shearer, 2000; Peffers et al., 2007; Chockalingam & Maathuis, 2022b) and the following research activities are taken:

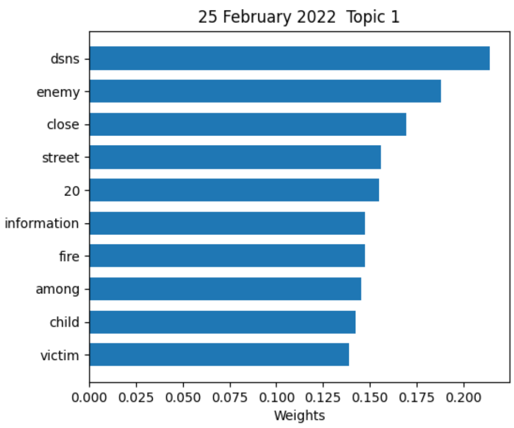
*Goal definition:* although during war, Telegram became increasingly used by Ukrainian and Russian communities, still a limited number of studies in the existing body of knowledge focus on Ukrainian users/speakers in more unconventional social media platforms like Telegram. Hence, this research aims to analyse the discourses, capture topics tackled, and their corresponding sentiments based on data collected in the first year of war, i.e., from February 24, 2022, until February 23, 2023.

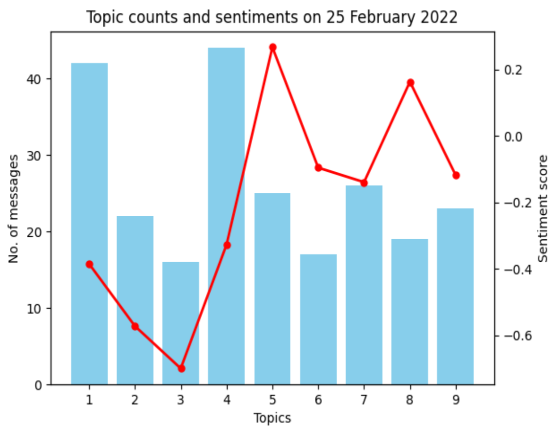
*Solution development:* the dataset contains 47483 messages in Ukrainian language which are translated using the Google Translate API, and further processed. This implies cleaning the data to remove aspects like unwanted duplicates, stop words, and punctuation. After performing PoS (Parts of Speech) tagging for gathering the grammatical function of a word in a sentence and lemmatization for capturing the semantic root of a word (lemma), the ML models are built for analysing the topics and sentiments using corresponding techniques. In topic modelling, the hidden thematic structure is captured by identifying and extracting topics as clusters of themes tackled in text while facilitating understanding the key structure of the discourses being analyzed (Zhao et al., 2021). Herein, the NMF (Non-negative Matrix Factorization) with Kullback-Leibler Divergence algorithm is applied for factorizing a document-term matrix that contains rows with documents, columns with terms, and cell values with term frequencies within documents. The matrix is split in two parts corresponding to document-topic and topic-term, fact that contributes to easily interpret the results obtained (Sokolova et al., 2016; Hien & Gillis, 2021; Maathuis & Kerkhof, 2023c). In sentiment analysis, the underlying emotional tone and emotions of users are captured through classification (Ates, E. C., Bostanci, E., & Guzel, 2021). In this research, the sentiments are classified as being negative or positive in respect to the topic and per day making use of pre-trained classifier Flair (Magajna, 2022; Maathuis & Godschalk, 2023).

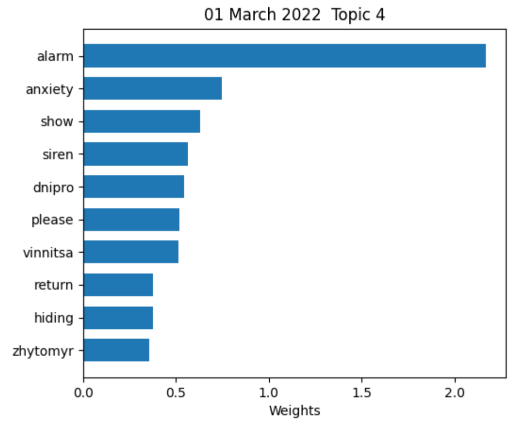
*Evaluation and communication:* the results of this research are positioned in the existing body of knowledge and ongoing public discourses in a transparent way (Maathuis & Chockalingam, 2022a), and the corresponding findings are communicated through scientific presentations and present article.

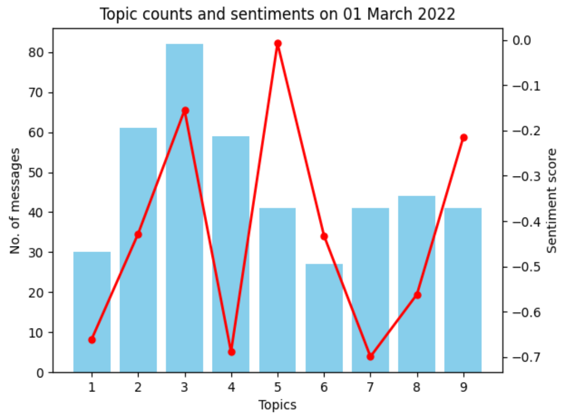
## 4. Results

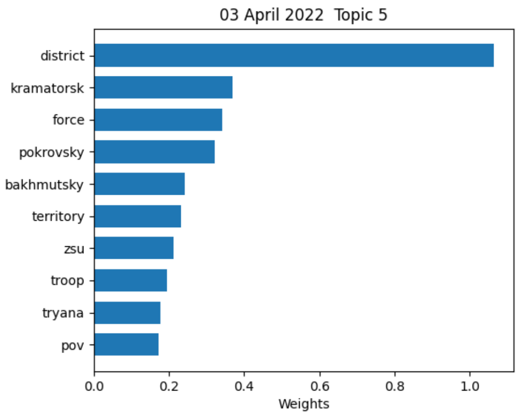
The results obtained from applying topic modelling and sentiment analysis are further presented. On this behalf, a selection of the results are structured in three categories. The first category captures on the left side a selection of nine topics discussed per day and on the right side counts topics and corresponding sentiments per day. For the whole year of study, a day was randomly selected to illustrate both topics and sentiments in Figure 1. Here, the topic numbers found at the bottom of the right image correspond to the topic number at the top of the left image. For instance, topic 1 has a negative sentiment score of -0.4. In the second category illustrated in Figure 2 are depicted words characterizing a topic together with their computed sentiment scores where a score of -1 means negative and +1 means positive for the whole time interval. And in the third category shown in Figure 3 are presented the sentiment scores per day for the whole year analysis.

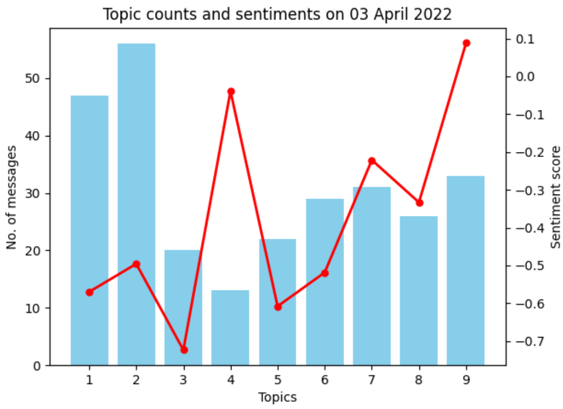


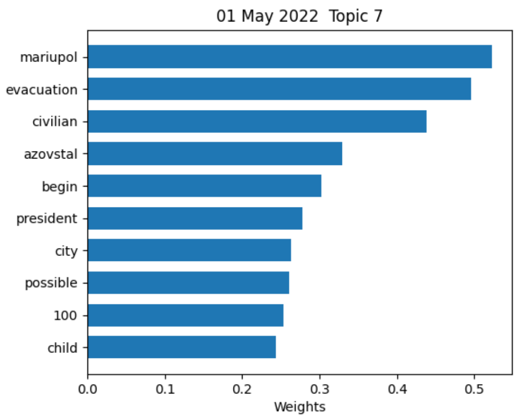



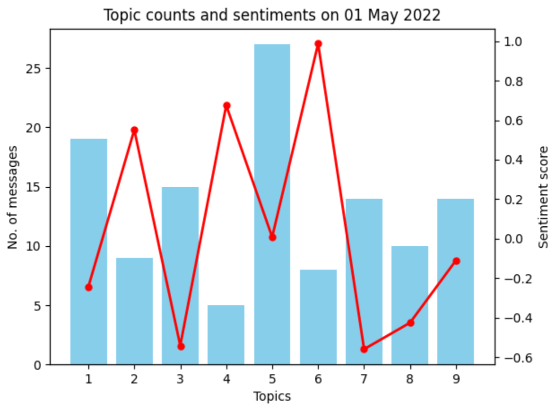

01 March 2022 Topic 4
alarm
anxiety
show
siren
dnipro
please
vinnitsa
return
hiding
zhytomyr
Weights

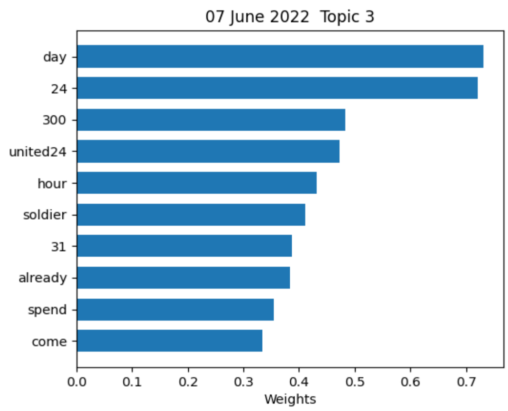

Topic counts and sentiments on 01 March 2022
No. of messages
Sentiment score
Topics

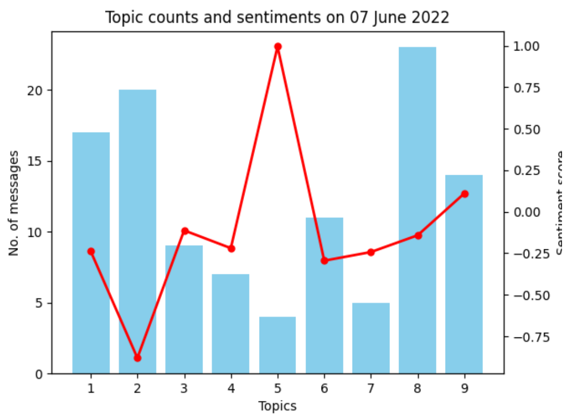

03 April 2022 Topic 5
district
kramatorsk
force
pokrovsky
bakhmutsky
territory
zsu
troop
tryana
pov
Weights

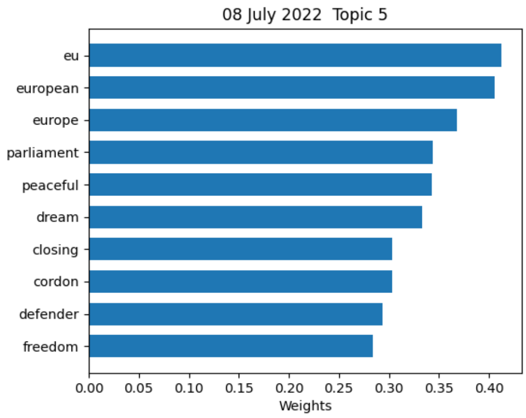

Topic counts and sentiments on 03 April 2022
No. of messages
Sentiment score
Topics

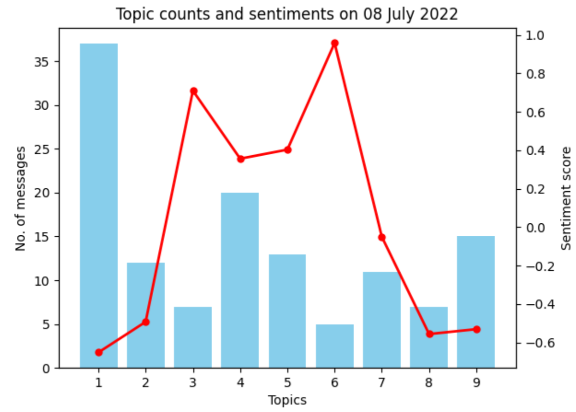

01 May 2022 Topic 7
mariupol
evacuation
civilian
azovstal
begin
president
city
possible
100
child
Weights

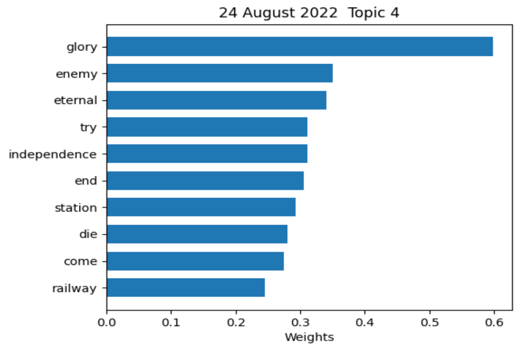

Topic counts and sentiments on 01 May 2022
No. of messages
Sentiment score
Topics

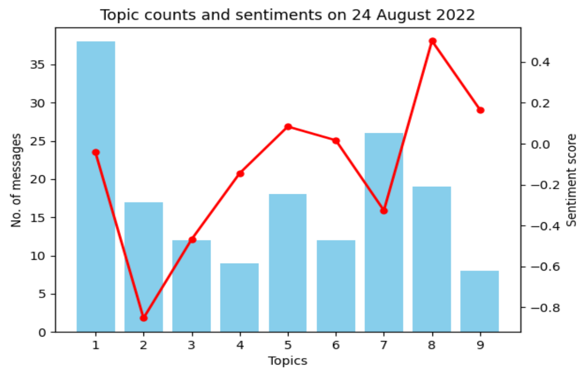

07 June 2022 Topic 3
day
24
300
united24
hour
soldier
31
already
spend
come
Weights


Topic counts and sentiments on 07 June 2022
No. of messages
Topics


08 July 2022 Topic 5
eu
european
europe
parliament
peaceful
dream
closing
cordon
defender
freedom
0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
Weights


Topic counts and sentiments on 08 July 2022
No. of messages
Sentiment score
Topics
1 2 3 4 5 6 7 8 9


24 August 2022 Topic 4
glory
enemy
eternal
try
independence
end
station
die
come
railway
0.0 0.1 0.2 0.3 0.4 0.5 0.6
Weights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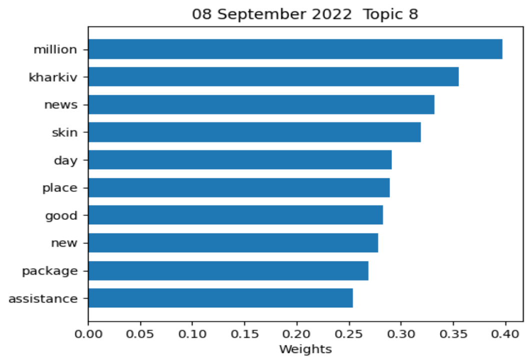
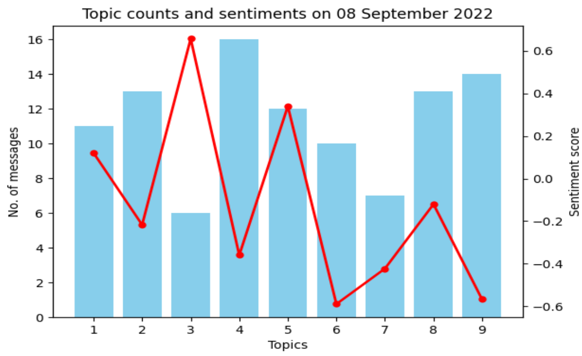
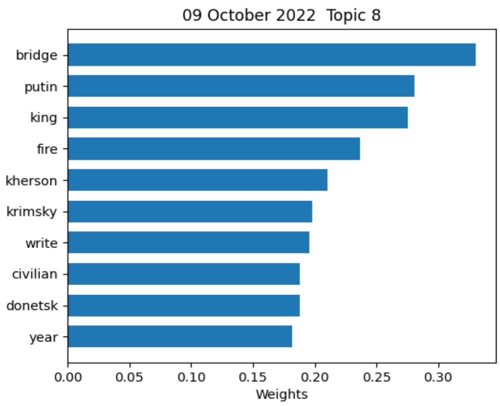
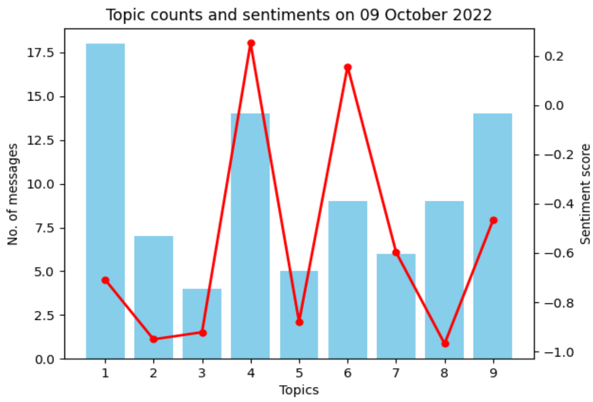
No. of messages
Sentiment score
Topics
1 2 3 4 5 6 7 8 9


08 September 2022 Topic 8
million
kharkiv
news
skin
day
place
good
new
package
assistance
0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
Weights


Topic counts and sentiments on 08 September 2022
No. of messages
Sentiment score
Topics
1 2 3 4 5 6 7 8 9


09 October 2022 Topic 8
bridge
putin
king
fire
kherson
krimsky
write
civilian
donetsk
year
0.00 0.05 0.10 0.15 0.20 0.25 0.30
Weights


Topic counts and sentiments on 09 October 2022
No. of messages
Sentiment score
Topics
1 2 3 4 5 6 7 8 9

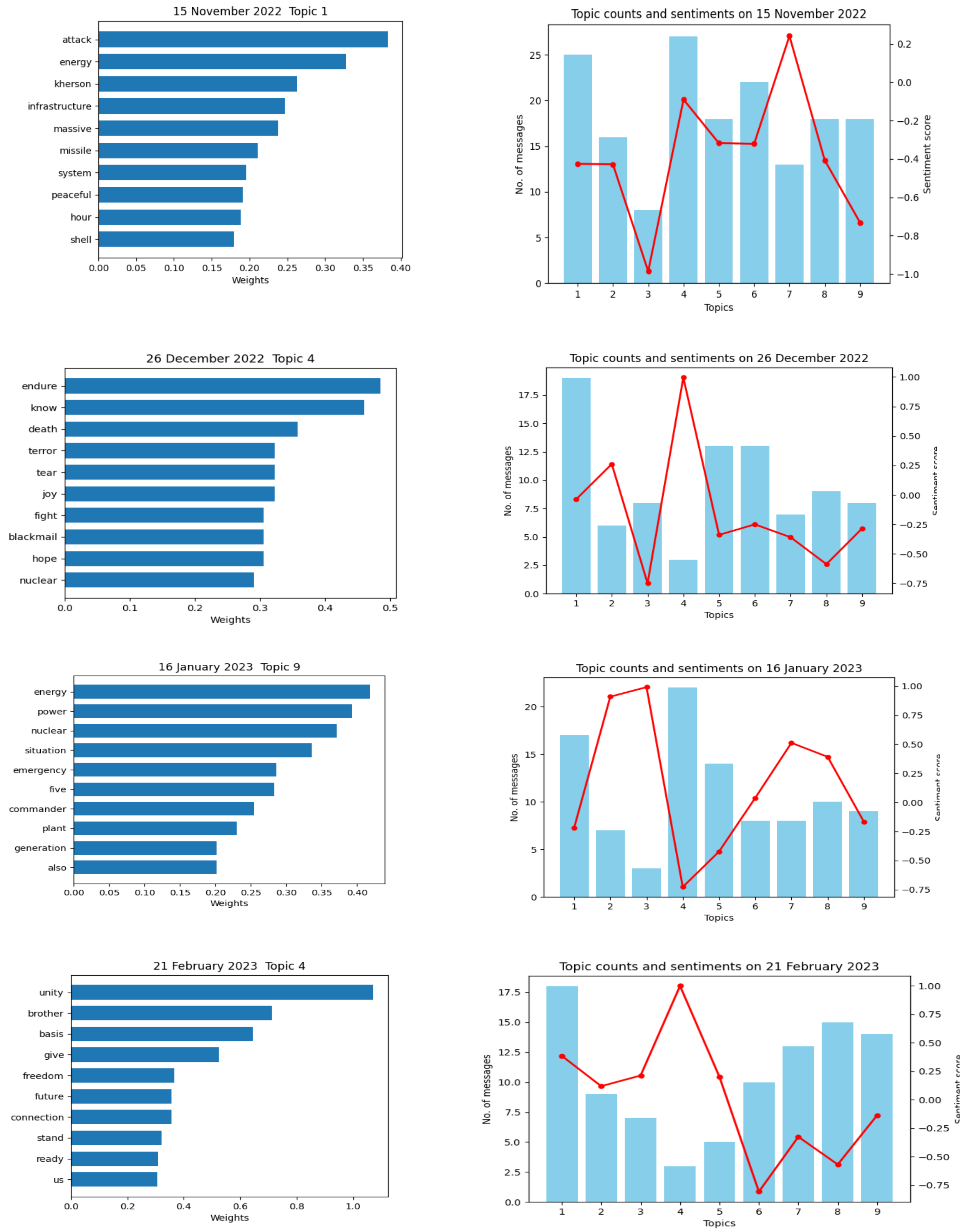



**Figure 1: Topics (left side) and topic counts (right side)**

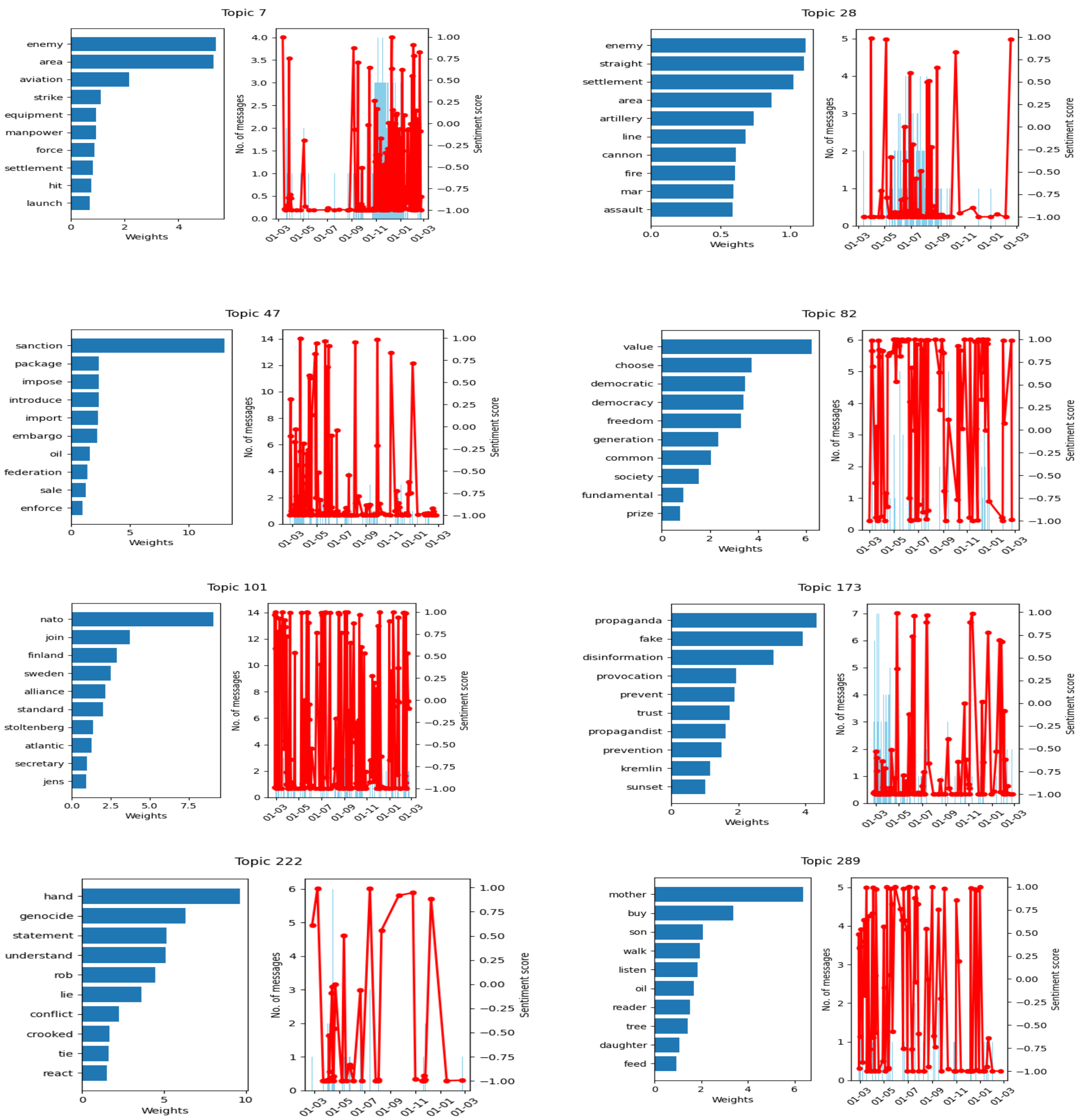



**Figure 2: Words for topic with corresponding sentiment scores**

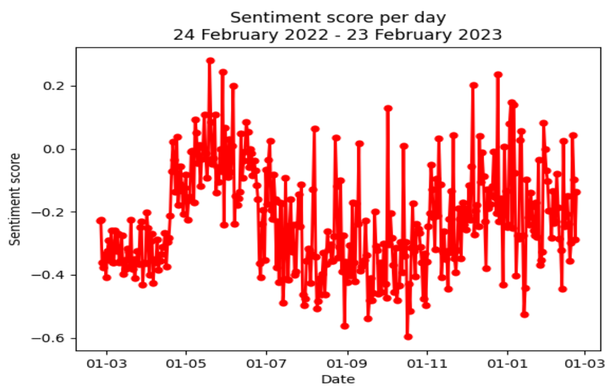



**Figure 3: Sentiment scores per day for the whole year analysis**

From these results, topics like enemy, victim, alarm, anxiety, territory, troop, Mariupol, president, child, evacuation, soldier, European, freedom, glory, independence, Kharkiv, assistance, civilian, Donetsk, bridge, Kherson, energy, missile, terror, nuclear, brother, and future, were identified. These topics match public and media discourses plus research and practitioner studies about the war in Ukraine since they capture war-related aspects, human emotions, and names of major cities that were severely affected (UN Secretary General, 2022; NATO, 2022; Levy & Leaning, 2022; Clark, 2023; NATO, 2023), and contribute to countering disinformation and misinformation efforts that aim at altering the public opinion regarding the events and impact characterizing this war and further creating confusion. Moreover, the general sentiment tendency is negative, but is explicable accounting the gravity of the events. Nevertheless, in some moments that have a direct real and more positive meaning, e.g., the Independence Day in Ukraine in August 2022 or the first visit of Biden in Kyiv in February 2023, a slight general tendency of higher sentiment scores is seen. This can be explained by the strength, resilience, and hope that Ukrainian people show in this trajectory.

## 5. Conclusions

The enduring Ukraine war has attracted substantial global media attention, became a crucial topic in strategic discourses and policies, and through different research and practitioner efforts, various and unique of its political, historical, and cultural angles were analyzed in diverse contexts (Hakimov & Cheema, 2023). Moreover, far-reaching implications like reshaping the power among nations, humanitarian aid, migration, and crisis environmental and climate policies e.g., energy transition programs are increasingly experienced (Wiertz, Kuhn & Mattissek, 2023). It is a complex conflict whose effects extend well beyond the battlefield, who captured an important segment of social media content (Agarwal, Punn & Sonbhadra, 2022) through topics like attacks, separation of families, lack of resources, poverty, and its global impact on multiple fronts (Lava et al., 2022). Nevertheless, while a large number of studies focused on platforms like Twitter and Facebook, less datasets are available and limited attention was given to studying discourses and feelings from unconventional and increasingly used platforms like Telegram and Reddit. On this behalf, this research tackles the existing knowledge gap of focusing exclusively on Ukrainian content about the war. It does that by conducting an in-depth analysis of discourses and corresponding sentiments of Ukrainian Telegram users by building ML models using the Design Science Research methodology in a Data Science approach.

The analysis is conducted on the first year of war, thus between February 24, 2022, to February 23, 2023. The results show a direct match between the discourses carried out in this platform and general media discourses by capturing both human and war-related topics. Additionally, taking into consideration the gravity of the events, a general negative tendency is noticed in the sentiments corresponding to the topics discussed. Further, this research directly contributes to ongoing efforts regarding building transparent and responsible AI-solutions for understanding the dynamics involved in the ongoing war in Ukraine and to supporting the efforts oriented to aborting or reducing social media manipulation mechanisms like disinformation and misinformation about the events, organizations, and people involved in this conflict. For further research, a call to building social media security awareness in time of conflict by developing transparent and responsible AI and gaming solutions is made. This can be done through a transdisciplinary research approach where efforts would be joined for building a safe, responsible, robust, and trustworthy digital domain.

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