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# Analyzing the worldwide perception of the Russia-Ukraine conflict through Twitter

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**Abstract**

In this paper, we analyze the worldwide perception of the Russia-Ukraine conflict (RU conflict for short) on the Twitter platform. The study involved collecting over 17 million tweets written in 63 different languages and conducting a multi-language sentiment analysis, as well as an analysis of their geographical distribution and verification of their temporal relationship to daily events. Additionally, the study focused on analyzing the accounts producing pro-conflict tweets to evaluate the possible presence of bots. The results of the analysis showed that the war had a significant global impact on Twitter, with the volume of tweets increasing as the war's threats materialized. There was a strong correlation between the succession of events, the volume of tweets, and the prevalence of a specific sentiment. Most tweets had a negative sentiment, while tweets with positive sentiment mainly contained support and hope for people directly involved in the conflict. Moreover, a bot detection analysis performed on the collected tweets revealed the presence of many accounts spreading tweets including pro-conflict hashtags that cannot be identified as real users. Overall, this study sheds light on the importance of social media in shaping public opinion during conflicts and highlights the need for reliable methods to detect bots.

**Keywords:** Sentiment analysis, Twitter, Russia-Ukraine Conflict, Dataset

## Introduction

Since the beginning of the 20th-century several significant global events such as wars, revolutions, and pandemics have affected the world. Just to mention a few, the First and Second World Wars, the Cold War, the Spanish and Asian pandemics. In recent years, the COVID-19 pandemic has disrupted daily life and habits, causing health and social problems for individuals and governments worldwide [1–3]. While the fight against COVID-19 continues, a new threat has rocked governments worldwide: the Russia-Ukraine conflict.

Unfortunately, as history teaches us conflicts have been an inherent part of human existence since the time of hunter-gatherers, and unfortunately, it seems that we have not yet been able to eliminate them. Whether fighting over food, borders, or power, war has been a constant presence in human life [4]. While people throughout history have tried to justify war in various ways, a real reason for it has never been found. Some have sanctified the methods and purposes of war, while others have seen it as the enemy of civilization. Margaret MacMillan argues that conflicts are an integral part of a country's and society's development [4]. However, one thing is certain: war has never had a positive impact on people.

In modern times, social networks have become crucial platforms for providing information and enabling people to express their opinions on various topics such as government decisions [5], school closures [6], climate [7], vaccines [8, 9], and more. As a result, we now have the ability to analyze user-generated content to assess public perception of specific events and issues. However, due to the abundance of content and account-related information, analyzing such data can be a challenging task, especially when multiple evaluation variables need to be taken into account.

In this paper, we do not discuss the reasons behind the conflict or provide any commentary on current events. Instead, our focus is on exploring the emotional impact of war through the lens of tweets shared by people from around the world. To this end, we present a dataset containing a large collection of posts collected from Twitter at the beginning of the conflict between Russia and Ukraine, and we discuss results obtained from different analysis tasks devoted to a multifaceted evaluation of the worldwide perception of the conflict. The dataset contains tweets collected using Twitter Streaming API with relevant keywords related to the war, and covers the period from February 25, 2022, to March 3, 2022, comprising more than 17 million tweets from 3,990,969 unique accounts and written in 63 different languages. Our analysis encompasses various aspects of the tweets, including frequency of hashtags, geographic distribution, and sentiment analysis in multiple languages. Such an analysis proved the worldwide impact of the RU-Conflict on the users' opinions. In fact, as the news concerning the main events began to spread, the volume of tweets increased on a global scale, with a sentiment that can vary either towards positive or negative sentiment according to the nature of the events reported. Additionally, we conducted an analysis of 20,474 accounts associated with 34,955 tweets including pro-conflict hashtags in order to identify the presence of bots on the social network and evaluate the effectiveness of social media campaigns in countering fake accounts.

Overall, the main goal of this research is to gain an understanding of how warfare is perceived in a broad context. To achieve this, we will conduct a thorough analysis that takes into account various factors, including geographical distribution, linguistic diversity, war-related events, and the use of automated content generation systems. By leveraging NLP-based sentiment analysis techniques, we aim to answer the following research questions (RQs):

- RQ1: To what extent do tweet sentiments vary based on either location or language?
- RQ2: How much war-related events impacted the number of tweets and the RU-Conflict perception?
- RQ3: What is the perception of the Russia-Ukraine conflict in public debates on Twitter, especially those of the people most involved in the conflict?
- RQ4: Is it possible to identify bots among Twitter accounts that spread opinions in favor of the war?

The main contributions of this paper can be summarized as follows:

- We provide a new dataset of tweets related to the Russia-Ukraine conflict containing over 17 million of posts shared by verified and unverified accounts. This dataset was collected by listening to the Twitter streaming service from the beginning of the conflict;
- We present a detailed analysis of tweet content to identify the most frequently used words and hashtags, aiming to examine the existence of positive and negative correlations between them when used in the same post;
- We conduct an extensive sentiment analysis of tweets in several languages, including geo-localization, providing an overview of the global perception of the Russia-Ukraine conflict. We also analyze the sentiment with respect to events that occurred during the initial phase of the conflict. The latter has also been deepened by specifically considering tweets written in Russian and Ukrainian languages or located in the Donbass area. An additional analysis seeks to classify the underlying opinions within tweets linked to Cyrillic hashtags according to a prompt-based strategy.
- We analyze the accounts spreading pro-conflict tweets to identify and evaluate the presence of bots designed to manipulate public opinion.
- We analyzed how the conflict's perceptions and debates changed one year later, by considering the 2023 tweets on the Russia-Ukraine conflict in the *Ukraine Conflict Twitter Dataset* [10].

The outline of this paper is as follows: Sect. "Related work" discusses work available in the literature concerning the analysis of social network discussions. Section "RU-Conflict dataset" presents an overview of the new dataset proposed in this study, along with a preliminary analysis of the tweets and commonly used hashtags. In Section "Analyzing the conflict perception in the RU-Conflict dataset", we present a worldwide geo-localized sentiment analysis in response to the four RQs introduced above. In Section "Analysis of public debates changes one year later" we present an analysis of public debates 1 year after the start of the conflict. Finally, Sect. "Conclusion and future works" outlines our conclusions and suggests potential future research directions.

## Related work

In recent years, social networks have attracted the attention of many users who use them not only for communication purposes, but also for following topic-specific discussions [11] expressing their viewpoints on global events [12, 13]. Moreover, social media networks have been found to be useful in supporting early warning systems for disaster relief agencies to obtain rapid disaster assessments. Among the various social media platforms, Twitter has emerged as one of the most widely-used microblogging platforms for sharing thoughts and opinions in response to current events. Twitter provides proper APIs that can be leveraged to gain insights into collective thinking about specific issues.

Until mid-2023, Twitter APIs enabled analysts to collect tweets together with account information. This also allowed researchers to focus on the problem of the potential disinformation spread by bots. Specifically, the social bot detection problem requires distinguishing between human and computer-controlled profiles. The diverse range of social bot types, products of human creativity, requires systems to learn their characteristics. To this end, many deep learning-based approaches have been defined in the literature, mainly including convolutional neural networks (CNN), long short-term memory (LSTM), and recurrent neural networks (RNN) [14]. In particular, as stated by Hayawi et al. CNNs typically excel in classifying textual content and identifying abusive language, angry terms, and named entities. On the other hand, LSTMs and RNNs are particularly valuable for understanding the relationship between consecutive time point data [15]. Among these, it is worth mentioning the approach outlined in [16] involves the integration of three LSTM models and a fully connected layer. Each of these models is dedicated to a distinct feature group, enabling the capture of complex social media behaviors. Additionally, BotRGCN, as presented in [17], stands out as one of the most effective bot detection frameworks available in current literature. It simultaneously encodes multi-modal user data, constructs a heterogeneous graph to represent real-world Twitter dynamics, and applies relational graph convolutional networks. Both above-described bot detection methods have proved to outperform Botometer v4 [18]. The latter represents the most popular state-of-the-art bot detection system.

Despite the possible presence of bots among social media accounts, user-generated content continues to represent a crucial source of information. In fact, numerous topic-specific datasets containing tweets and account features from the social network platform have been used to conduct various analyses of user-generated content related to specific topics. As an example, in [19] Effrosynidis et al. present a detailed examination of public opinions on climate change using Twitter. In [20], Dooms et al. propose an analysis of tweets related to movie ratings to enhance movie recommender systems utilizing natural language processing techniques. Additionally, sentiment analysis of tweets has been used in sports analytics decision models to predict match and point spreads in the English Premier League [21].

Numerous studies have gone beyond collecting opinions on general topics and have conducted various analyses on the impact of events occurring during a particular period. For example, Ibrahim and Wang [22] examined tweets associated with leading UK retailers during the Black Friday to Christmas and New Year's sales period to comprehend the underlying content within a large corpus of unstructured text, with the goal of improving online retailing services and engaging with customers. The COVID-19 pandemic has been one of the most extensively analyzed recent events, with numerous works published on its impact using social media networks [23]. Multiple Twitter datasets have been created to evaluate users' perceptions and sentiments regarding the pandemic's progression [2, 24]. Other studies have focused on analyzing the misinformation spread on Twitter and other social media platforms to exacerbate negative emotions [25, 26]. Furthermore, the COVID-19 topic has been employed as a case study for developing novel analysis models, such as identifying relevant influencers [27] and detecting emotions [28], among others.

The analysis of user-generated content on Twitter has also been devoted to political discussions [29]. For example, researchers have investigated the impact of politicians' tweets, specifically those of former US President Donald Trump, on financial markets [30]. Moreover, political discussions are commonly analyzed to predict election outcomes (see [31] for a review). Sentiment analysis of tweets has also been used in crisis situations, such as in [32], where a crowd sentiment detection model was introduced to detect public emotions during calamitous events. In contrast, the Syrian refugee crisis was analyzed in [33], where Turkish and English tweets were compared to identify differences in sentiment. Researchers have been paying attention to sentiment analysis on microblogging platforms across various languages and application domains, including politics [34], product reviews [35], and health crises [36], among others.

Finally, the Russia-Ukraine conflict has led to the proliferation of many topic-specific tweets. As a result, several focused datasets have emerged in the literature to perform proper analysis, as highlighted in previous studies [37, 38].

As for our aim, in the last year, other works proposed sentiment, emotion, and/or intention analysis over user-generated content concerning the Russia-Ukraine conflict in order to deepen the war perception [39], by also using ML-based strategies [40] or defining proper models, as for the MF-CNN-BiLSTM model defined by Aslan [41]. Most of them exploit Twitter API and/or previously published tweets' datasets. Instead, the Reddit.com social network has been involved in [42], to specifically measure hope and fear within users' posts of the first 3 months of the conflict through a dictionary-based analysis. The authors also used the Latent Dirichlet Allocation (LDA) algorithm to perform a topic modeling analysis revealing that the presence of geopolitical arguments exhibits a correlation with both hope and fear. However, these works have either presented tweet datasets with basic statistics or have focused on generally classifying the sentiments and emotions over the considered datasets, or by considering specific users and their political affiliations. In contrast, to the best of our knowledge, the current study offers a more comprehensive analysis that aims to evaluate users' perceptions of the RU-Conflict. The study incorporates over 17 million multi-language tweets directly collected from the Twitter streaming APIs and provides extensive sentiment analysis of the language and their geographical distribution, as well as their contextual categorization with respect to conflict-related opinions. Moreover, this study also represents the first proposal evaluating the presence of bots among accounts sharing Russia-Ukraine conflict-related content.

## RU-Conflict dataset

In this section, we first provide an overview of the RU-Conflict dataset, by describing the different types of tweets extracted from Twitter and the strategy for collecting them. Then, we analyze the most frequent hashtags used in the tweets, also showing statistics about them, and discussing their correlation with the aim of performing a preliminary analysis of people's collective thoughts.

### Overview of RU-Conflict dataset

To collect tweets, we used the keyword-based approach by considering a set of keywords related to the Russia-Ukraine conflict. Initially, we manually extracted a small set of popular keywords from the most commonly used hashtags on Twitter using online services, such as Tweeplers[1]. We then used the Twitter Streaming API and the initial set of keywords to collect tweets for a single day, with the goal of identifying additional keywords that co-occur with the initial set. We considered a set of more than 25 keywords that are frequently used in tweets around the world, including terms such as "`UkraineUnderAttack`", "`RussiaUkraineConflict`", "`Zelensky`", or "`Putin`". Starting from

[1] Tweeplers.

**Table 1** Details of RU-Conflict dataset

| | Before hydrating | After hydrating |
|---|---|---|
| Number of tweets | 17,393,039 | 17,045,908 |
| Tweets from non-verified accounts | – | 16,785,937 |
| Tweets from verified accounts | – | 259,971 |
| Accounts with location | – | 2,316,555 |
| Average tweets per account | – | 4.27 |
| Most recent tweet | 2022-03-03 | |

the set of keywords, through the Twitter APIs we were able to collect a large number of tweets related to the Russia-Ukraine conflict. It is important to notice that, Twitter APIs are not limited to extracting only tweets that contain the specified keywords, but they find a tokenized match of keywords within the body of a Tweet, extracting a larger set of tweets than the hashtags-based approach[2]. Thanks to this, the RU-Conflict dataset contains a large collection of tweets written in different languages, which also include keywords written in other alphabets, such as Cyrillic. The resulting dataset, called RU-Conflict, and the list of initial keywords used for tweet collection are publicly available on GitHub's official repository[3].

Table 1 shows statistics on tweets extracted before and after the hydration process. As we can see, we have collected 17,045,908 tweets including 259,971 from verified accounts and 16,785,937 from non-verified accounts. Starting from this collection of tweets, we have performed cleaning operations of the contents by removing all special characters, yielding the standardization of the tweet syntax. After standardizing the content of tweets, it was possible to identify the most common hashtags used in the tweets and analyze their frequency in the dataset. In particular, we used a specific regular expression to identify and collect hashtags, which allowed us to standardize the syntax of the hashtags, which often are syntactically different due to the use of uppercase and/or lowercase letters, such as in the case of "`StayWithUkraine`" and "`Staywithukraine`" or "`Peace`" and "`PEACE`".

Figure 1 reports the occurrences of the different types of tweets shared by verified and non-verified accounts. As we can see, among the different types of tweets, there are about 13 million of them that are retweets, which represents 76% of all tweets. Moreover, 1,434,862 tweets contain at least one mention of other accounts (8% of all tweets), and about 3 million of tweets are Plain Text Tweets, i.e., tweets that are not retweets and do not contain mentions that are written in a standard text-based format (15% of all tweets).

## Correlation and statistical analysis

The concept of hashtags arises from the need to create specific labels capable of concisely expressing thoughts and quickly sharing them with other people. In the case of Twitter, the functionality of a hashtag is twofold: (i) identifying the main topic of the tweet, and (ii) allowing the connection between people who have used the same hashtag.

[2] Building queries for Search Tweets - www.developer.twitter.com.

[3] https://github.com/DastLab/RU-Conflict-Twitter-dataset.

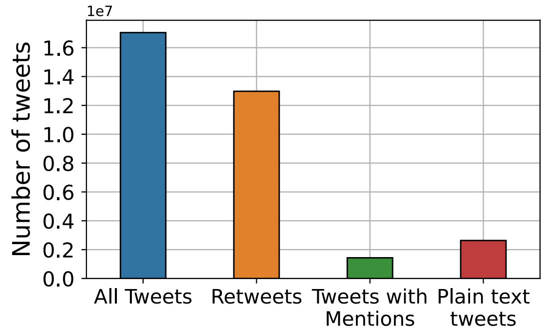


**Fig. 1** Types of tweet in RU-CONFLICT

In both cases, the hashtag creates a stream of posts concerning the same topic to gather user opinions and points of view on the same issue.

In our dataset, we have collected 307,055 different hashtags that have been used 29,820,401 times in over 17 million tweets. These statistics show the importance that hashtags have for people when expressing positive and negative thoughts in tweets, leading people to use more of them in the same tweet.

Table 2 shows the occurrences and the frequencies of the most used hashtags written in both Latin and Cyrillic alphabets. The occurrence values represent the total number of times a hashtag appears, while the frequency is the number of occurrences of each hashtag with respect to the tweets shared from both verified and non-verified accounts. It is important to notice that only 11,767,496 of 17,045,908 tweets contain at least one hashtag, which corresponds to 69% of all the tweets. As shown in Table 2, we have defined three different frequency values that represent the frequency of each hashtag with respect to (i) the number of all the hashtags used in the tweets (i.e., $N_X$); (ii) the number of tweets that contain at least one hashtag (i.e., $N_Y$), and (iii) the number of all tweets in the data collection (i.e., $N_Z$). Let $N$ be the number of occurrences of each hashtag in the data collection, the frequencies are formally defined as:

$$F_1 = \frac{N \cdot 100}{N_X} \qquad F_2 = \frac{N \cdot 100}{N_Y} \qquad F_3 = \frac{N \cdot 100}{N_Z} \tag{1}$$

As we expected, there are a large number of tweets that contain general hashtags that refer to Ukraine and Russia, such as "`#ukrainerussia`", "`#russiaukrainewar`", "`#украина (#ukraine)`", "`#россия (#Russia)`", and so forth. However, several hashtags show strong anti-conflict sentiments, such as "`#stopputin`", "`#stoprussia`", "`#standwithukraine`", "`#нетвойневукраине (#nowarinUkraine)`", "`#нетвойне (#nowar)`", and "`#противвойны (#anti-war)`", which represent about 8.79% of all the hashtags used in the tweets. Moreover, as we can see, these hashtags are contained in approximately 17.92% of the tweets of users who have used at least one hashtag in their posts, and 12.76% of the entire collection of tweets. It is important to note that, among the most used hashtags, there are no pro-conflict hashtags, i.e., hashtags that clearly express an opinion in favor of the Russia-Ukraine conflict. These initial statistics allow us to estimate how much the war has aroused strong anti-conflict thoughts in people around the world.

**Table 2** The most used hashtags in the Latin and Cyrillic alphabets in the streaming data collection

| Latin alphabet | | | | | Cyrillic alphabet | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Hashtag | N | $F_1$ (%) | $F_2$ (%) | $F_3$ (%) | Hashtag | N | $F_1$ (%) | $F_2$ (%) | $F_3$ (%) |
| #ukraine | 5,955,147 | 20.26 | 50.76 | 34.94 | #нетвойне (#Nowar) | 63,891 | 0.21 | 0.54 | 0.37 |
| #standwithukraine | 314,028 | 1.07 | 2.68 | 1.84 | #укра (#ukra) | 58,529 | 0.2 | 0.5 | 0.34 |
| #russia | 1,545,860 | 5.26 | 13.18 | 9.07 | #против (#against) | 41,476 | 0.14 | 0.35 | 0.24 |
| #ukrainerussia | 312,396 | 1.06 | 2.66 | 1.83 | #украина (#Ukraine) | 23,308 | 0.08 | 0.2 | 0.14 |
| #putin | 986,260 | 3.36 | 8.41 | 5.79 | #россия (#Russia) | 12,776 | 0.04 | 0.11 | 0.07 |
| #anonymous | 247,337 | 0.84 | 2.11 | 1.45 | #всрф (#vsrf) | 11,979 | 0.04 | 0.1 | 0.07 |
| #kyiv | 638,271 | 2.17 | 5.44 | 3.74 | #нетвойневукраине (#nowarinUkraine) | 9,609 | 0.03 | 0.08 | 0.06 |
| #ucrania | 207,879 | 0.71 | 1.77 | 1.22 | #славаукра (#slavaukra) | 7,551 | 0.03 | 0.06 | 0.04 |
| #ukrainerussiawar | 549,428 | 1.87 | 4.68 | 3.22 | #харьков (#Kharkiv) | 5,674 | 0.02 | 0.05 | 0.03 |
| #ukraineinvasion | 186,176 | 0.63 | 1.59 | 1.09 | #ки (#ki) | 5,368 | 0.02 | 0.05 | 0.03 |
| #stopputin | 479,403 | 1.63 | 4.09 | 2.81 | #харк (#hark) | 5,230 | 0.02 | 0.04 | 0.03 |
| #russiaukraineconflict | 177,166 | 0.6 | 1.51 | 1.04 | #нет_войне (#Nowar) | 4,852 | 0.02 | 0.04 | 0.03 |
| #ukraineunderattack | 432,614 | 1.47 | 3.69 | 2.54 | #потерьнет (#lose) | 3,939 | 0.01 | 0.03 | 0.02 |
| #nato | 169,276 | 0.58 | 1.44 | 0.99 | #новости (#news) | 3,705 | 0.01 | 0.03 | 0.02 |
| #stoprussia | 426,473 | 1.45 | 3.63 | 2.5 | #путин (#Putin) | 3,642 | 0.01 | 0.03 | 0.02 |
| #russiaukraine | 149,949 | 0.51 | 1.28 | 0.88 | #россиясмотри (#Russialook) | 3,400 | 0.01 | 0.03 | 0.02 |
| #nowar | 385,962 | 1.31 | 3.29 | 2.26 | #киев (#Kyiv) | 3,225 | 0.01 | 0.03 | 0.02 |
| #war | 147,753 | 0.5 | 1.26 | 0.87 | #нетвойн (#nowar) | 3,115 | 0.01 | 0.03 | 0.02 |
| #russiaukrainewar | 370,078 | 1.26 | 3.15 | 2.17 | #война (#war) | 3,020 | 0.01 | 0.03 | 0.02 |
| #ukrainian | 135,380 | 0.46 | 1.15 | 0.79 | #рос (#grewup) | 2,947 | 0.01 | 0.03 | 0.02 |
| #ukrainewar | 361,952 | 1.23 | 3.08 | 2.12 | #херсон (#Kherson) | 2,929 | 0.01 | 0.02 | 0.02 |
| #prayforukraine | 126,923 | 0.43 | 1.08 | 0.74 | #нетвойнесукраиной (#thereisnowarwithUkraine) | 2,781 | 0.01 | 0.02 | 0.02 |
| #kiev | 353,493 | 1.2 | 3.01 | 2.07 | #нато (#NATO) | 2,689 | 0.01 | 0.02 | 0.02 |
| #stopwar | 125,494 | 0.43 | 1.07 | 0.74 | #противвойны (#anti-war) | 2,525 | 0.01 | 0.02 | 0.01 |
| #russian | 336,102 | 1.14 | 2.86 | 1.97 | #рф (#rf) | 2,019 | 0.01 | 0.02 | 0.01 |
| #breaking | 111,966 | 0.38 | 0.95 | 0.66 | #нетвойнес (#nowarness) | 1,842 | 0.01 | 0.02 | 0.01 |
| #zelensky | 315,696 | 1.07 | 2.69 | 1.85 | #буча (#butch) | 1,839 | 0.01 | 0.02 | 0.01 |
| #europe | 100,953 | 0.34 | 0.86 | 0.59 | #япротиввойны (#Iamagainstthewar) | 1,736 | 0.01 | 0.01 | 0.01 |

**Table 2** (continued)

| Latin alphabet | | | | | Cyrillic alphabet | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Hashtag | N | $F_1$ (%) | $F_2$ (%) | $F_3$ (%) | Hashtag | N | $F_1$ (%) | $F_2$ (%) | $F_3$ (%) |
| #kharkiv | 315,179 | 1.07 | 2.69 | 1.85 | #русские (#Russians) | 1,650 | 0.01 | 0.01 | 0.01 |
| #putinwarcriminal | 80,399 | 0.27 | 0.69 | 0.47 | #мол (#theysay) | 1,547 | 0.01 | 0.01 | 0.01 |

Aiming to analyze how sentiments influenced collective opinion, we performed a correlation analysis between the most used hashtags in tweets within the entire dataset. To identify the correlation between these hashtags, we converted them into a vector form. In particular, we created a binary vector for each tweet, where the dimensions were equivalent to the number of hashtags present in the tweet. Each element of the vector was assigned a value of 1 if the corresponding hashtag was present in the tweet, and 0 otherwise. As an example, let us consider the hashtags "#nato", "#saynotowar", "#saveinnocentlives", "#europe", "#russiaukraineconflict", and "#humanityfirst", then the tweet:

> *"War never guarantees lasting peace but lasting death, it's the humanity that dies a painful death. Why on earth the innocent and non-combatant bear the brunt. Peace and dialogue must prevail! #SayNoToWar #RussiaUkraineConflict #HumanityFirst #SaveInnocentLives"*

will be represented as [0, 1, 1, 0, 1, 1] in its vector form.

In this analysis, we started by considering the top-100 hashtags in Latin and Cyrillic alphabets, i.e., the ones that appear in the highest number of tweets. This means that, for each tweet, we defined a binary vector of size 200, each representing a row and a column of a binary matrix. Thus, the correlation between hashtags has been computed by using the Pearson coefficient[4], which returns a value in the range between [−1.0, 1.0] for each matrix element, i.e., a pair of hashtags. Among the resulting values, we selected the hashtags that contain the most relevant correlation values, i.e., those that express interesting strong and weak correlations, obtaining a set of 35 hashtags. Figure 2 shows the correlation matrix and the resulting values of the considered hashtags.

Concerning results, as we expected, there are several strong correlations between hashtags in the same domain, such as "#ucrania" with "#rusia", "#украина (#Ukraine)" with "#россия (#Russia)", and "#russianukrainianwar" with "#russians". However, the analysis reveals many other strong correlations, especially among hashtags written in Cyrillic, such as the ones between "#stopputin" with "#safeairliftukraine", "#stoprussia" and "#europe", and "#против (#against)" with "#нетвойне (#nowar)", and "#nowar" with "#против (#against)". In fact, these strong correlations clearly express the anti-conflict sentiment that resides in the people who wrote the tweets, regardless of their nationality or country. Furthermore, other interesting strong correlations have been provided by the hashtags "#europe" and "#stopputin" and "#stoprussia". This shows that many people from different countries associate the end of the conflict with

[4] The Pearson coefficient measures the degree of the association involving linear related variables [43].

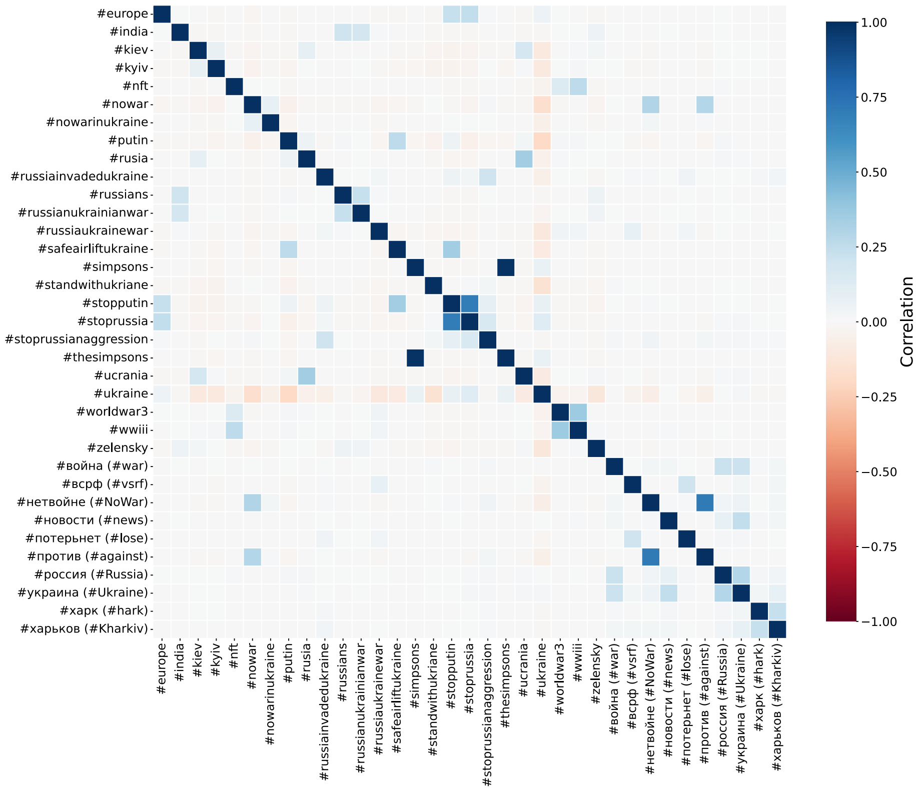


**Fig. 2** Correlation matrix of the most used hashtags in tweets

Europe, which could have a significant influence to make NATO intervene in favor of Ukraine. On the other hand, there are some interesting weak negative correlations concerning the hashtag "`#ukraine`" with "`#putin`", "`#standwithukriane`", "`#nowar`", and "`#russiaukrainewar`", and "`#stoprussia`", and "`#putin`". In fact, although we would have expected a strong correlation between these hashtags, their negative correlations describe how negatively the idea of war is viewed, especially when associated with Ukraine.

## Analyzing the conflict perception in the RU-Conflict dataset

In this section, we will describe the extensive sentiment analysis performed on a portion of the RU-Conflict dataset. Our primary objective is to investigate and answer our RQs by evaluating the tweets' expressions of positive, negative, and neutral sentiments. Moreover, we will present contextual analysis performed with Dolly 2.0 [44], a new open-source Large Language Model (LLM), aiming to identify the context of tweets associated with Cyrillic hashtags and provide insights on the tweets written by people who are indirect protagonists of the conflict.

The analyzed portion of the RU-Conflict dataset covers the events that happened during the initial days of the conflicts, in particular, the period going from February 25th to March 3rd, 2022. Figure 3 summarizes the most significant events reported by the media, extracted by a web search on the main newspapers. In the early days, news of

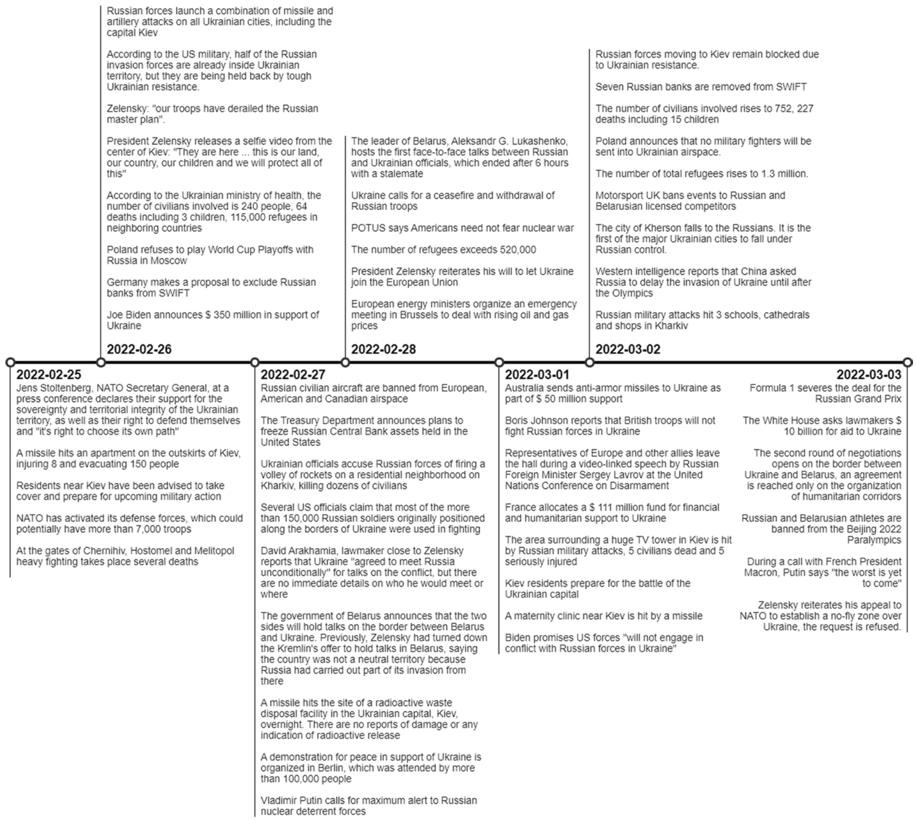


**Fig. 3** Timeline of events that occurred during the 1st week of the conflict

Russian attacks on cities near Kyiv[5] was interspersed with statements from world leaders, who affirmed their commitment to support the Ukrainian people[6] and impose economic sanctions on Russia[7,8]. As the number of refugees and casualties increased, the international community intensified the sanctions, severing all ties with Russian-linked entities such as banks[9], airlines[10], athletes[11,12], events promoters[13], and so forth, which were in any way linked to Russia[14]. Mediation efforts between the two nations were also made during this time[14], including two rounds of negotiation talks, but both proved unsuccessful[15,16].

The events surrounding the war in Ukraine have gained global attention, with a significant amount of tweets being collected in a dataset. This calls for a comprehensive

[5] Source: www.tribuneindia.com
[6] Source: www.reuters.com
[7] Source: www.whitehouse.gov
[8] Source: www.bloomberg.com
[9] Source: www.euronews.com
[10] Source: www.wsj.com
[11] Source: www.autosport.com
[12] Source: www.euronews.com
[13] Source: www.formula1.com
[14] Source: www.reuters.com
[15] Source: www.nbcnews.com
[16] Source: www.twitter.com

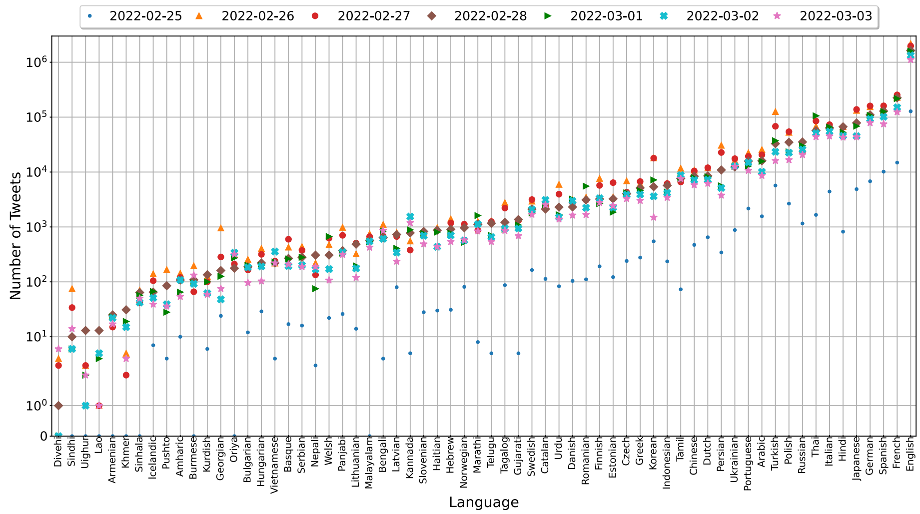


**Fig. 4** Statistics on the language of the tweets

analysis of the sentiments conveyed in microblogging texts. Several research questions need to be addressed, such as the language and geographical distribution of tweet sentiments, the correlation between events and sentiments over time, and the potential existence of fake texts generated by non-human sources. The following sections provide details on these research questions, the specific analysis processes designed to answer them, and a discussion of the obtained results.

### RQ1: To what extent do tweet sentiments vary based on either location or language?

To answer RQ1, we have conducted sentiment analysis on the tweets collected, taking into consideration various tweet and account features, such as tweet language and location. Details on the analysis methods and the obtained results are provided in the following.

*Multi-language Sentiment Analysis* As first analysis, we conducted a sentiment analysis on the RU-Conflict dataset by taking into account the language specificity of tweets. Since the dataset includes over 17 million tweets from all over the world, we had to account for the significant differences in language. Figure 4 describes the number of tweets posted in the considered period (from February 25th to March 3rd, 2022), and we identified a total of 63 languages. To maintain the representation of minority languages, we intentionally excluded English tweets from the plot, as they were significantly more numerous than the other languages, with a peak of 9,958,016. Including English tweets in the plot would have flattened the lines of minority languages, making it challenging to perceive the differences.

Regarding some of the observations that can be made from Fig. 4, a common trend across all languages is an increase in the volume of tweets as the days progress. Specifically, the volume of tweets posted on the RU-Conflict on February 25th, 2022 (represented by the red line) is consistently lower across all languages than the other days. It appears that at this point, people may not have fully comprehended the severity of the events and their potential implications. Interestingly, although there is a preference for

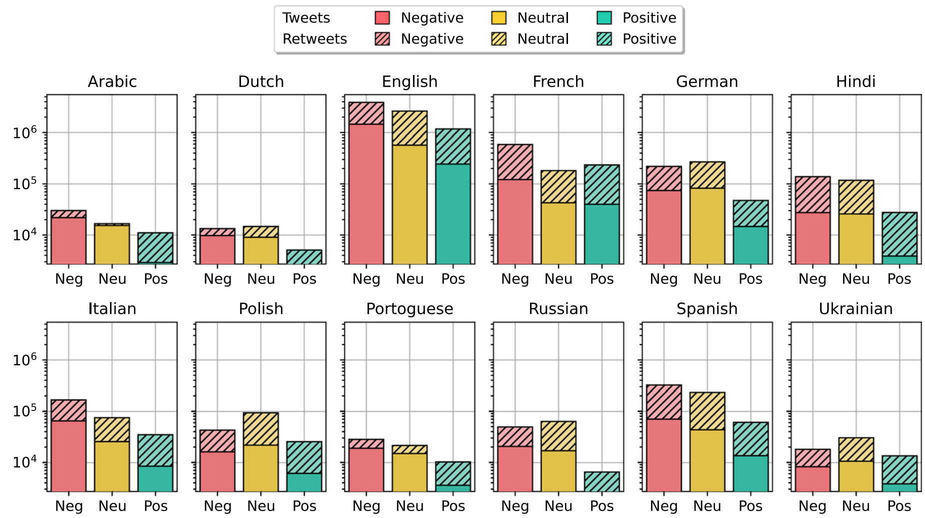


**Fig. 5** Statistics of multi-language sentiment analysis

the "majority" languages spoken worldwide, such as German, Spanish, French, Hindi, and Portuguese, other languages such as Serbian, Tagalog, Japanese, and Icelandic also contributed significantly to the overall volume of tweets during the initial period of the RU-Conflict. This suggests that the events were already perceived as a global phenomenon affecting everyone, without exception.

Due to this variability in languages found within the RU-Conflict dataset, we were obliged to select a subset of them following a trade-off between the number of tweets and the availability of libraries supporting the sentiment analysis for such languages. To this end, we selected a total of 12 languages (see Figure 5) and performed a multilingual sentiment analysis employing a specific set of libraries supporting each of them. The total number of tweets in the considered languages is 14,055,251, which corresponds to approximately 81% of the total tweets.

The sentiment analysis for all languages has been performed by using *XLM-Roberta* [45]. The latter is based on Google BERT (Bidirectional Encoder Representations from Transformers) [46], which represents a bidirectional model capable of identifying the meaning of words by considering only the other words contained in a sentence. BERT has been designed to be easily fine-tuned for multiple tasks, like language inference and it has been already trained on a huge number of texts in different languages.

Figure 5 provides an overview of how sentiment is distributed among the considered languages. In particular, we plotted histograms counting the amount of positive, negative, and neutral tweets and retweets for each language.

In this context, tweets with a positive sentiment can express support, optimism, or approval regarding certain aspects of the conflict. This could include tweets expressing hope for a peaceful resolution, admiration for acts of kindness or cooperation, or positive views toward the country's army, humanitarian efforts, and diplomatic initiatives. Conversely, tweets with a negative sentiment typically convey disapproval, criticism, frustration, anger, or sadness related to the conflict. This may encompass tweets condemning acts of violence, expressing concern for civilian casualties, criticizing political decisions or actions, or expressing anger towards any party involved. Instead, tweets with a neutral sentiment are those that do not express a clear positive or negative stance regarding the Russia-Ukraine conflict. They might provide factual information, updates, or observations without conveying a strong emotional tone or bias.

Findings showed an equal distribution between negative and neutral sentiment, with a slightly lower volume of positive sentiment tweets. Moreover, as we can see, most of the analyzed tweets are retweets and the majority of them are verified for all languages, especially when considering the positive sentiment. In fact, most languages show that the number of retweets with positive sentiment is higher than tweets, especially for Arabic, Dutch, Hindi, Portuguese, Russian, and Ukrainian languages. This suggests that users who want to spread positive sentiment prefer to share tweets written by others or respond to existing posts with positive comments. These findings regarding tweets with positive sentiment tweets prompted us to manually analyze some of the positively classified tweets. The analyzed tweets and retweets have shown messages of support for the people affected by the war, indicating that many users focused on providing hope to the downtrodden citizens rather than criticizing the offenders.

*Geo-localized Sentiment Analysis* To complement our multilingual analysis, we conducted a worldwide geo-localized sentiment analysis to investigate how tweets were distributed across the globe while still distinguishing between positive, neutral, and negative sentiments. To achieve this, we used the `Location` field that users may fill in to indicate where they are tweeting from. However, Twitter does not verify the accuracy of these locations, so we filtered the tweets used for sentiment analysis to exclude those with fake or non-specific locations such as "Wonderland" or "here". This filtering procedure reduced the total number of tweets analyzed from 14,055,249 to 12,780,183, which we then plotted on a world map.

The distribution of tweets across the globe is visualized in Fig. 6. The world map is divided into rectangular areas based on the longitude and latitude coordinates of the tweets, allowing us to group them and generate a bar chart for each area. The bar chart displays the number of tweets collected in each area for each sentiment category, with the color scheme distinguishing between positive (green bar), neutral (yellow bar), and negative (red bar) sentiment. Moreover, the size of the bar chart and the label on top indicate the number of tweets collected in that area.

Concerning results, as we expected, there is a particularly high presence of tweets in densely populated areas, i.e., Europe, UK, USA, and Southeast Asia. These findings partially confirm the results of the previous analysis, where English-speaking countries tended to lean towards negative or neutral sentiment, but also had a significant number of positive sentiment tweets. On the other hand, some discrepancies were observed when comparing the results with those presented in Fig. 5. For instance, when evaluating European countries with a high percentage of people speaking Polish, Ukrainian, and Russian, and the two primary Portuguese-speaking countries, i.e., Portugal and Brazil, we can note that the high predominance of tweets with a neutral sentiment, which was observed in the previous sentiment analysis (see Fig. 5), is not evident. This difference is due to the filtering process mentioned earlier. In fact, further manual analysis revealed that tweets in Polish, Ukrainian, Russian, and Portuguese were among the most excluded ones due to empty `Location` fields.

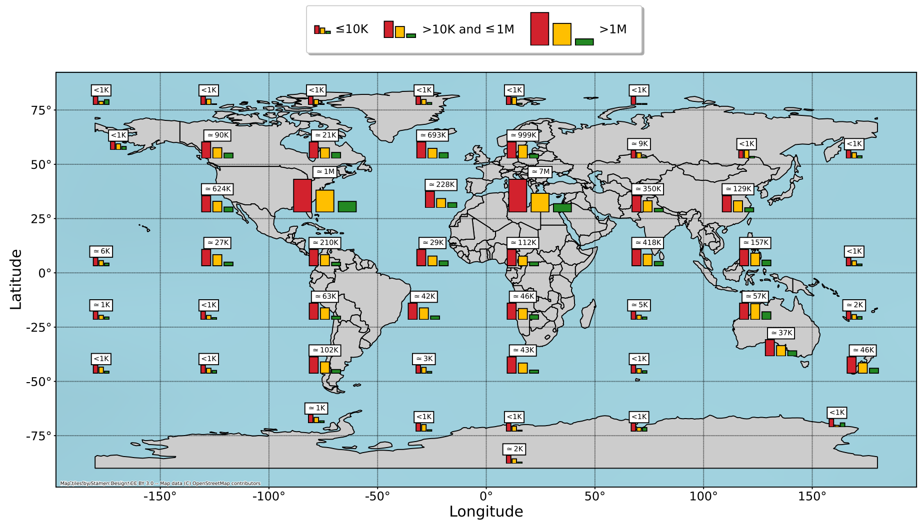


**Fig. 6** Geo-localized sentiment analysis of the considered tweets

Overall, our sentiment analysis showed a predominance of tweets with negative sentiments regardless of both language and geographical position. It is worth mentioning that the tweets with negative sentiment resulted being less than what we would have expected. In fact, the volume of tweets with negative sentiment throughout the areas rarely goes above 50% of the total.

### RQ2: How much war-related events impacted the number of tweets and the RU-Conflict perception?

To answer RQ2, we evaluated the variation in the average number of positive and negative tweets over time. Figure 7 provides an overview of both positive (represented by the blue line) and negative (represented by the red line) sentiment during the early days of the RU-Conflict. As expected, the number of tweets with negative sentiment is almost always higher than the number of positive ones, and we observe a general upward trend in the number of posted tweets as time passes. Moreover, we cross-checked some of the peaks with the significant events that occurred during that period. In particular, the increase in both positive and negative tweets during the early hours (GMT) of February 28th, 2022 coincided with the publication of news announcing the start of the first round of negotiations between Russia and Ukraine[17].

On the other hand, the peak of negative sentiment tweets in the period between the end of February 28th and March 1st, 2022 coincided with the publication of news announcing that the negotiations had failed[18]. Another peak of negative tweets was observed in the early hours of March 2nd, 2022 which appears to correspond with the reports from American officials suggesting that China had prior knowledge of the Russian invasion plans months before the conflict began[19].

It is worth noting that during the late hours of March 3rd, 2022, the number of positive tweets surpassed that of negative ones. Upon further investigation, we found that

[17] Source: www.npr.org

[18] Source: www.kyivindependent.com

[19] Source: www.nytimes.com

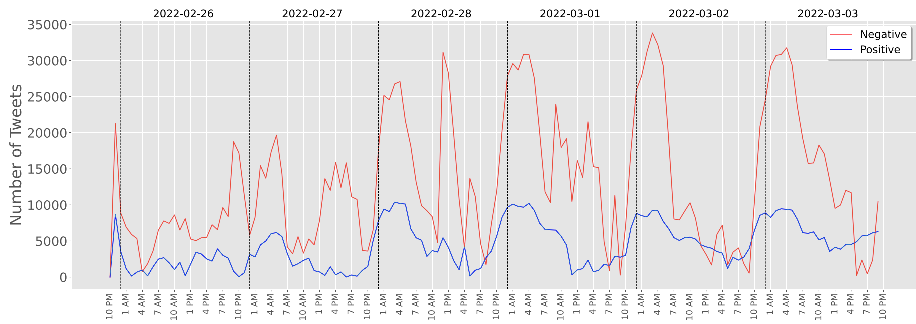


**Fig. 7** Sentiment analysis overview

this coincided with a tweet from the Adviser to the Head of the Office of President of Ukraine regarding the results of the second round of negotiations between Russia and Ukraine that, although did not lead to a complete resolution of the conflict, at least allowed to reach an agreement on the organization of humanitarian corridors to rescue civilians[20]. Unfortunately, this positive trend was short-lived as the day ended with an increase in the number of negative tweets. This may have been due to news published about a call between Emmanuel Macron and Vladimir Putin, during which the Russian president stated that "the worst is yet to come"[21].

The analysis suggests that the number of tweets related to the RU-Conflict is affected by events that occur during the early days of the conflict. The volume of tweets generally increases over time, but peaks are observed when certain news is published by the media. The sentiment of the tweets also varies depending on the nature of the news. Events associated with a possibility of resolution tend to result in more positive sentiment tweets, while news about increasing loss and conflict exacerbation results in more negative sentiment tweets.

**RQ3: What is the perception of the Russia-Ukraine conflict in public debates on Twitter, especially those of the people most involved in the conflict?**

To answer RQ3, we conducted two different analyses focused both on tweets written in the Ukrainian and Russian languages and on those containing hashtags written in the Cyrillic alphabet in order to gauge the opinions of the people most impacted by the conflict.

The first analysis focused on tweets originating from Ukraine and Russia. For this analysis, we plotted the distribution of the tweet on a world map, highlighting the associated sentiments[22]. By means of this analysis, we intend to gain further insight into the global distribution of tweets in Ukrainian and Russian languages.

The second analysis focused on tweets containing hashtags written in the Cyrillic alphabet. For this analysis, we tried to investigate the context of the tweets by exploiting a Large Language Model (LLM) in order to gain deeper insights into the discussions within this subset of tweets.

*Sentiment Analysis of tweets written in Russian and Ukrainian languages* In this analysis, we tried to investigate the perception of the conflict among the most affected people, by analyzing tweets written in Russian and Ukrainian languages. Furthermore,

[20] Source: www.twitter.com

[21] Source: www.edition.cnn.com

[22] An interactive version of these maps is available on the official GitHub repository

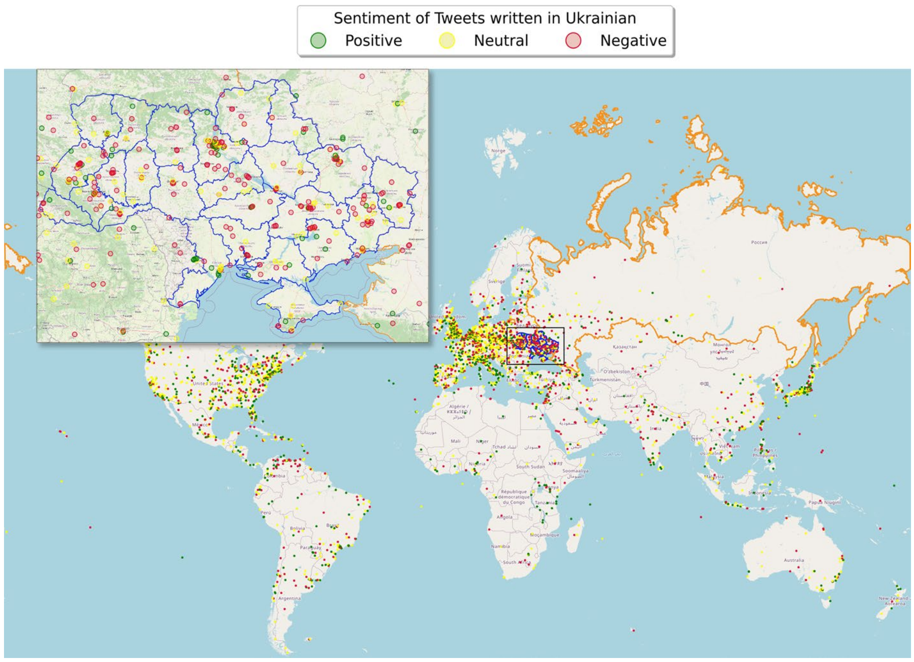


**Fig. 8** Geo-localized sentiment analysis of tweets in Ukrainian

through the analysis of the geographical origin of the users who wrote tweets, we focused our discussion on those originating from the area of conflict.

Figure 8 shows the results obtained for Ukrainian tweets. Overall, it highlights that the majority of Ukrainian tweets are either positive or neutral, with most of them originating from locations outside of Ukraine, including Europe, Japan, and the USA. This could be due to the support of the Ukrainians abroad or foreigners who choose to express their solidarity with Ukraine in the local language. However, when focusing on the tweets originating from within Ukraine, despite being in a few quantities, the sentiment leans more toward negativity.

Table 3 reports the most representative examples of tweets located in Ukraine. pertaining to different sentiments and written in either Ukrainian or Russian. The first two rows, which consist of tweets written in Ukrainian, show that while one tweet motivates the army to not surrender, the other expresses concerns and the grim reality of the conflict.

Figure 9 shows the results obtained for Russian tweets, which exhibit a negative sentiment, unlike the Ukrainian tweets. Once again, the majority of these tweets are situated outside of Russian territories, mainly in Europe, Turkey, and the USA. This suggests that people want to directly convey their opposition to the Russian political choices. Moreover, by focusing on tweets located in the conflict area (i.e., Ukraine), we observe that the few tweets are mainly located in Kyiv and the territories most affected by the conflict (i.e., Donbass), with the majority expressing negative sentiment.

Concerning the most representative tweets located in Ukraine and written in the Russian language, i.e., the last two rows in Table 3, they present similar arguments to those written in Ukrainian. The positive tweets express a desire to defend Ukraine, while the negative tweet expresses concerns against the war. It is likely that these tweets were

**Table 3** Examples of tweets from Ukraine written in Ukrainian and Russian

| Language | Sentiment | Tweet | Tweet (English) |
|---|---|---|---|
| Ukrainian | Positive | *"Рекомендую до просмотру та поширення!! Слава Україні!! Слава Збройним Силам України!! #SlavaUkraini #StandWithUkraine."* | *"Recommend to watch and share!! Glory to Ukraine!! Glory to the Armed Forces of Ukraine!! #SlavaUkraini #StandWithUkraine."* |
| Ukrainian | Negative | *"Вони гірше звірів, бо вбивають не з необхідності, а просто тому що можуть. Дякувати богу, людина в авто наче вижила, пишуть."* | *"They are worse than animals, because they kill not out of necessity, but simply because they can. Thank God, the person in the car seems to have survived, they say."* |
| Russian | Positive | *"Обычный житель Киева, который тоже готов защищать нашу Украину. Вільна Україна #UkraineRussiaWar #Kyiv #Ukrania"* | *"An ordinary resident of Kyiv, who is also ready to defend our Ukraine. #UkraineRussiaWar #Kyiv #Ukrania"* |
| Russian | Negative | *"#Ukraine Снова впадаю в истерику и хочу, чтоб это всё прекратилось и было, как раньше. Но, как раньше уже ничего не будет."* | *"Again I fall into hysterics and I want it all to stop and be like before. But, as before, nothing will be."* |

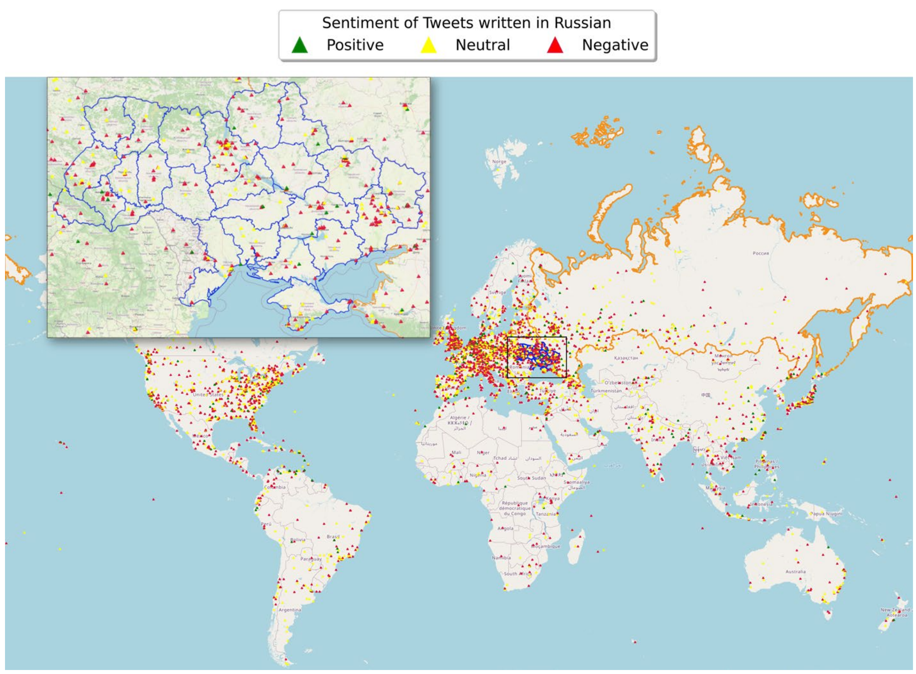


**Fig. 9** Geo-localized sentiment analysis of tweets in Russian

written by Ukrainian people who want to make their thoughts clear to Russian people. Although we expected some pro-conflict tweets originating from pro-Russia regions in the Donbass area, also following several newspaper articles[23][24], these types of tweets did not emerge in our analysis. This may be due to a twofold aspect. The first aspect to consider is that the process of identifying the place of origin of the tweets considered the user's location, which was the only location information available related to the tweets. This has led to some tweets written in Russian, where the user's location was not

[23] www.washingtonpost.com/politics/
[24] www.aljazeera.com/news/

specified. The second aspect may concern the impact of the conflict on the local population. The people who wrote from these regions probably first thought about finding safe havens, regardless of political alignment, and then about sharing messages in support of Russia but not necessarily conflict actions. In general, this absence of pro-war sentiment in tweets from the Donbass area highlights the complex and multifaceted nature of public sentiment, where even within conflict zones different perspectives can exist.

*Contextual Analysis of tweets containing hashtags written in the Cyrillic alphabet* As discussed above, in this analysis, we have tried to delve deeper into the content of the tweets to investigate the opinions held regarding the Russia-Ukraine conflict. To this end, we employed Dolly 2, a recently proposed open-source LLM, trained on a huge set of high-quality data generated by people [44]. Through the knowledge behind the LLM, we aimed to extract more information from the tweets and to investigate more precisely public opinions on the Russia-Ukraine conflict.

We used two distinct prompts defined on the basis of the *Manual Template Engineering* approach, which is considered one of the approaches for defining prompts that are most natural and close to people's requests based on human introspection [47]. The two templates for the prompts have been defined as follows:

**Prompt 1**: Does the content of this tweet support actions to resist the conflict? [T][A]
**Prompt 2**: Does the content of this tweet express a desire to stop the conflict? [T][A]

The first prompt aims to evaluate whether the content of a tweet expresses a position in line with the promotion of messages of resistance to the Russia-Ukraine conflict. Instead, the second prompt aims to verify whether the content of a tweet conveys the intention or desire to put an end to the Russia-Ukraine conflict.

Figure 10 shows the statistics about the answers provided by Dolly for the considered prompts.

As we expected, for Prompt 1, most of the tweets written in Ukrainian and in all other languages express messages of encouragement to resist conflict. Many Ukrainians, in fact, may support actions to resist the conflict as it reflects their desire to protect their army and territorial integrity. Moreover, because many of the Ukrainian tweets have been shared by other countries (Fig. 8), probably by emigrant citizens, they contain messages of support for friends and family stranded in Ukraine. Regarding tweets written in other languages, the positive results achieved by our analysis can show the solidarity that most people in the world have towards those involved in the conflict.

The two interesting results for Prompt 1 are the number of tweets written in Ukrainian that do not support conflict resistance actions and those written in Russian that do support them. In the first case, several tweets express messages against the behavior of the Russian citizens, asking them to stand against their government with protests. Instead, some of them express the will that the Russian people can experience the same hardship as the Ukrainian people in wars, asking their army to attack Russian cities. In other tweets about this case, they express opinions against the cruelty of the Russian army, inciting the Ukrainian army not to have remorse when attacking their opponents. These tweets likely arise from Ukrainians' anger towards the conflict and the actions it has caused.

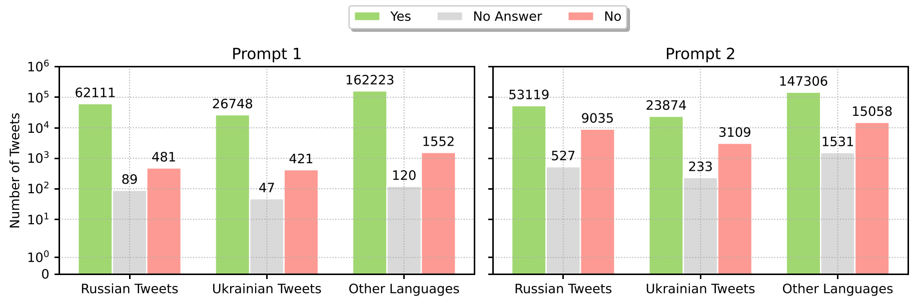


**Fig. 10** Statistics of the context-based analysis

Concerning tweets written in Russian that express support for actions to resist the conflict are of a different nature. A part of the tweets aims to provide warning messages to Ukrainian citizens about the decisions of the Russian government, urging them to resist the current situation. Other tweets in this case address the Russian people themselves, highlighting that they are not responsible for the conflict and that they themselves must resist all restrictions imposed by the Russian government since the beginning of the conflict. Instead, some of them contain news about the resistance actions of Ukrainian citizens against the Russian army, expressing support for Ukrainian actions. Some examples of Ukrainian and Russian tweets are shown in Table 4.

Concerning Prompt 2, as we can see from Fig. 10, the positive number of tweets that explicitly express the intention to stop the conflict is much greater than the other answers. This observation is particularly evident in the number of tweets shared in languages other than Russian and Ukrainian, which is a symbol of the widespread international concern and support for ending the conflict.

Among the interesting results achieved by Prompt 2, there are many tweets with a negative answer, especially in tweets written in Ukrainian and Russian. Regarding the tweets in Ukrainian, as we expected, many tweets express a desire for anger towards the Russian government. Other tweets contain news and messages to the Ukrainian people about humanitarian interventions from other nations, such as food distribution or safe places to take refuge. Instead, many of them contain news retweeted from official pages of newspapers and TV or requests for help from NATO and world powers. However, as we expected, none of these tweets express a thought in favor of the continuation of the conflict, but rather, as we also saw from the analysis of Prompt 1, many tweets in Ukrainian that had a negative response to Prompt 2 want the attacks to be addressed to the Russian government. Probably, these tweets stem from the frustration of Ukrainians in response to the conflict and its resulting consequences.

Concerning tweets written in Russian with negative responses to Prompt 2, similar to tweets in Ukrainian, many of them contain news or closeness messages to the Ukrainian people. Some other tweets contain thoughts against the Russian government, expressing words of anger against the military and government systems. It is important to note that these messages were shared before communications controls were imposed in Russia, which is why they often contain strong words against the government. However, among the tweets in Russian that do not express a desire to stop the conflict, there are also messages that support government choices and the

**Table 4** Some examples of tweets extracted from the RU-Conflict dataset and analyzed with the LLM

| | | Tweet | Tweet (English) | Answer |
|---|---|---|---|---|
| Prompt 1 | Ukrainian | *"я хочу щоб росіяни відчули те ж саме що ми зараз. з москви пітеру з цих заспокоєний міст з комфортним життям. я хочу, щоб наші війська пульнули ракети в тому напрямку, я хочу щоб вони відчули, як це чути вибухи і розуміти, що твоє життя більше ніколи не буде як раніше #україна"* | *"I want the Russians to feel the same as we do now. from Moscow to Peter from these calm cities with a comfortable life. I want our troops to shoot missiles in that direction, I want them to feel what it's like to hear explosions and understand that your life will never be the same again #ukrainia"* | No |
| | | *"нелюди... не забудемо, не пробачимо! хлопці, не беріть полонених. смерть російським окупантам! #україна #рф #війна #ukrainerussiawar"* | *"inhumans... we will not forget, we will not forgive! guys, take no prisoners. death to the Russian invaders! #україна #рф #війна #ukrainerussiawar"* | No |
| | Russian | *"местные жители в черниговской области не пустили технику оккупантов и они уехала обратно под границу глуши, не пали соляру, а то потом не уедешь #украина #война #ukraine #ukrainerussiawar #warinukraine #stopwar #standwithukriane"* | *"Local residents in the Chernigov region did not allow the equipment of the invaders to enter and they drove back to the border of the wilderness, don't fall to the diesel fuel, and then you won't leave #украина #война #ukraine #ukrainerussiawar #warinukraine #stopwar #standwithukriane"* | Yes |
| | | *"мы все знаем, что русский народ не несет ответственности за #украинскую #войну. но русский народ должен активно сопротивляться и продолжать требовать окончания #войны!!"* | *"We all know that the Russian people are not responsible for the #Ukrainian #war. but the Russian people must actively resist and continue to demand the end of the #war!!"* | Yes |
| Prompt 2 | Ukrainian | *"почуйте нас! для нас зараз дуже важливо, щоб #нато закрило нам небо від літаків, ракет, вертольотів. допоможіть нам з небом! #ukrainians_asks #nato_to_being_their_forces_to #ukraine at least to close the sky. to give shelter from the sky #help_us_in_the_sky"* | *"hear us out! it is very important for us now that #nato close our sky from planes, missiles, helicopters. help us with the sky! #ukrainians_asks #nato_to_being_their_forces_to #ukraine at least to close the sky. to give shelter from the sky #help_us_in_the_sky"* | No |
| | Russian | *"когда там уже этот русский мир наступит? а то пока что только русскую разруху видела... #россия #украина #ukraine #istandwithputin"* | *"When will this Russian peace come there? and so far I have only seen Russian devastation... #Russia #Ukraine #ukraine #istandwithputin"* | No |
| | English | "`#istandwithputin` and I guess every sane mind should stand with Putin. watch this video and decide by yourself, what you have done, if you be at the place of president @kremlinrussia_e `#istandwithrussia #russia #русский #русскийсолдат #русскийвоенный #america #americaterror`" | – | No |

Russia-Ukraine conflict. These tweets are present both in tweets written in Russian and in tweets in other languages and containing Cyrillic hashtags. Some examples of these tweets are shown in Table 4.

It is important to notice that, among the analyzed tweets written in all languages, i.e., Russian, Ukrainian, and other languages, many of them analyzed by the LLM are retweets. This can be due to the fact that people often use retweets as a means for sharing public news or amplifying their support or agreement with the original tweet, without needing to compose a new message. Therefore, the number of retweets in the dataset can indicate the level of resonance of content expressing opinions or news events, regardless of the language in which they are expressed. Furthermore, as we can see from Fig. 9, a part of the tweets do not have any associated response from the LLM (Grey bars). This is due to the fact that some tweets are mostly composed of hashtags or emoticons, or do not contain information related to the prompt under analysis. In both cases, the LLM was unable to provide a useful answer for the purpose of our analysis.

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The sentiment analysis, performed on tweets written in Russian and Ukrainian language, shows that there is a significant distribution of both Ukrainian and Russian-language tweets outside of Ukraine. The sentiment of Ukrainian tweets is predominantly positive or neutral, while Russian tweets are predominantly neutral or negative. However, there is no big difference in the sentiment of tweets posted in Ukraine, whether in Ukrainian or Russian. These tweets are published mainly in the capital and Donbass areas and express a predominantly negative sentiment. Instead, the contextual analysis of tweets composed in Russian, Ukrainian, and other languages shows that the majority of these tweets contain messages of resistance to war actions and messages expressing a desire to put an end to the Russia-Ukraine conflict. Furthermore, many of the tweets that express none of this, contain opinions against the cruelty of the conflict and the armies or express a desire for anger toward the Russian government.

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**RQ4: Is it possible to detect bots among Twitter accounts that spread opinions on behalf of the war?**

Following the geo-localized sentiment analysis, it is evident that social media has emerged as an influential platform for expressing public opinions and propagating personal viewpoints for or against political decisions. In recent years, citizens have leveraged social media platforms to disseminate ideas and perspectives among communities, sometimes in opposition to the governments of various nations[25]. This has led to individuals infiltrating democracies of many countries via social media, using fake accounts that appear to belong to real citizens to spread extremist views against their countries[25]. Major social media companies like Facebook and Twitter, prompted by the EU and other governments, have already taken action to curb this propaganda on their platforms.

Starting from these considerations, to answer RQ4, we deepened our analysis by evaluating pro-conflict hashtags using the strategy proposed in [48]. In particular, from the complete collection of tweets, we extracted their associated hashtags and manually selected those that are pro-conflict, i.e., those that promote or support Russia's actions in the conflict (see Table 5). We then identified 34,955 tweets containing at least one of these hashtags, which were written by 20,474 distinct users. This allowed us to evaluate each user and determine how many of them were suspected of being bots.

To conduct this analysis, we considered two different types of approaches widely employed in the classification of bots on social media, namely *Botometer* and *BotRGCN*. *Botometer*, defined by Observatory on Social Media (OSoMe) at Indiana University [49, 50], leverages machine learning techniques to determine whether an account is a bot or a human account by calculating a rating score. The higher the score, the higher the probability that the account is a bot. Botometer uses multiple models trained on various types of bots and human accounts and returns the scores from each model to compute an overall score between 0 and 5. A score of 0 indicates that the account is likely real, while a score of 5 indicates that it is most likely a bot. Botometer can be queried by contacting the API endpoints passing the basic information of the user account to classify.

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[25] Source: www.bloomberg.com

**Table 5** List of considered pro-conflict Hashtags

| Pro-conflict Hashtags | | |
|---|---|---|
| #belarusiswithputin | #idonotstandwithukraine | #isupportru |
| #belausstandwithputin | #iostoconputin | #isupportrus |
| #brazilwithputin | #istandwithputin | #isupportrusia |
| #brazilwithrussia | #istandwithrus | #isupportrussia |
| #chinastandsbyrussia | #istandwithrusia | #isupportvladimirputin |
| #chinastandwithputin | #istandwithrusia | #lsandwithputin |
| #chinasupportrussia | #istandwithrussia | #notstandwithukraine |
| #chinasupportsputin | #istandwithrussiaarmy | #prowar |
| #comboversstandwithputin | #istandwithrussiafedera-tion | #prowarmedia |
| #iamsupportrussia | #istandwithrussianbots | #prowarnecrophile |
| #iamwithputin | #istaywithputin | #prowarnecrophiles |
| #iamwithrussia | #isupportputin | #wesupportrussia |
| #славароссии | #путинмойпрезидент | #путинлучший |
| #россияспутиным | #россиянепротивпутина | #россиянененавидятпутина |

Note: #славароссии: #GlorytoRussia | #путинмойпрезидент: #Putinismypresident | #путинлучший: #Putinisthebest | #россияспутиным: #RussiawithPutin | #россиянепротивпутина: #RussiaisnotagainstPutin | #россиянененавидятпутина: #RussiansdonothatePutin

Such information is then integrated with further details obtained through the Twitter APIs, enabling the classification of the account. Hence, through Botometer we were able to identify four types of bots[26]:

- **Astroturfing**: bots involved in specific campaigns that have been conceived by interest groups and/or companies to spread consent or dissent of a product, an idea, and/or an event;
- **Fake follower**: bots that have been purchased to increase follower counts;
- **Self declared**: bots included into botwiki.org;
- **Spammer**: bots already labeled as spambots from several datasets;
- **Other**: either bots that have been obtained from manual annotation, user feedback, and so forth or accounts that cannot be classified due to them being suspended or banned.

Among all the information obtained by Botometer, we considered the "overall" score to determine which account could be classified as bots (i.e., those with an overall score of 3 or greater) and assigned them to different categories based on the type of bot that scored the highest. We then determined the number of tweets posted by real accounts and each category of bots, segmented by day throughout the analysis period.

BotRGCN (Bot detection with Relational Graph Convolutional Networks) is a framework for the identification of Twitter Bots which recently affirmed itself as one of the most accurate ones [51]. In particular, it tackles the identification of both by utilizing both numerical and categorical user property items while also encoding the user's tweets using pre-trained language models. Furthermore, it reinforces the classification

[26] "Botometer FAQs"

by producing a graph structure from the Twitter network and then applying relational graph convolutional networks. Unlike what happened with Botometer, for employing BotRGCN in the identification of bots among the accounts we considered, we were required to train the model upon a labeled dataset of bots. To this end, we decided to employ the Twibot-22 dataset [52], which as of to date represents the largest benchmark, labeled dataset, for bots available in the state of the art, comprising 1,000,000 users and 86+ million tweets. Thus, we performed the training phase of BotRGCN on Twibot-22 and then employed the trained model over the 20,474 distinct users, seeking bots. As for the Botometer analysis, we then cross-referenced the classified accounts with respect to the tweets they posted within the analysis period. Two important aspects are worth mentioning when highlighting the differences between Botometer and BotRGCN, in the first place BotRGCN can only provide a binary classification, i.e., whether the account can be identified as a bot or not, and secondly, BotRGCN solely relies on the information gathered from the training set and classifies considering only the features fed to the trained model, not requiring any further information to be retrieved by means of the Twitter APIs.

Table 6 reports statistics on the pro-conflict hashtags analyzed according to both the detection approaches we considered. In particular, we reported the number of tweets posted for each account category during the analysis period, differentiating tweets from retweets. As expected, among the accounts that have posted pro-conflict hashtags, both approaches associated the highest rate of pro-conflict tweets to real accounts, even though the presence of about 33% of tweets associated with non-real accounts reveals that information on social networks is often disrupted by fake accounts. war[27].

In terms of the accounts identified as bots by Botometer, the highest volumes of tweets are posted by accounts linked to *Astroturf* bot type which, as aforesaid, is typically used to promote a specific idea or message related to military campaigns. Another type of bots that posted frequently during the analysis period is the *Fake Follower*. The latter can be acquired for just a few dollars [53] and used to disseminate fake information or conduct propaganda campaigns. Interestingly, *Self Declared* and *Spammer* bots have a much lower number of tweets shared compared to other types. This is likely because these types of bots are easily identifiable and blockable by Twitter, resulting in their reduced usage. An important volume of tweets is then associated with the *Other* type. As previously stated, such type of classification for a specific account might be provided due to the fact that such an account might have been banned, or suspended, by Twitter. This makes it impossible for Botometer to retrieve, through the Twitter APIs, the further information required to complete the classification. Thus, such a high number of the *Other* type accounts identified, especially as the days pass by and the volume of tweets increases, might suggest that such accounts could have been banned by the social network due to their extolling the conflict.

The comparison between Botometer and BotRGCN revealed an interesting detail regarding the distribution of tweets that can be associated with humans or bots. In fact, in spite of the fact that BotRGCN conducts an exclusively binary classification, we can see that when we add up the number of tweets associated with bots

[27] Source: www.abc.net.au

**Table 6** Statistics on Pro-conflict Hashtags

| Approach | Type | #Tweets | #Tweets per day | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 02-25 | | 02-26 | | 02-27 | | 02-28 | | 03-01 | | 03-02 | | 03-03 | |
| | | | TW | RT | TW | RT | TW | RT | TW | RT | TW | RT | TW | RT | TW | RT |
| Botometer | Human | 16,860 | 21 | 20 | 791 | 726 | 979 | 604 | 797 | 630 | 1,338 | 1,065 | 1,624 | 3,393 | 2,126 | 2,746 |
| | Astroturf | 7,734 | 5 | 8 | 342 | 363 | 464 | 335 | 415 | 297 | 698 | 418 | 788 | 1,147 | 945 | 1,509 |
| | Fake Follower | 3,439 | 2 | 5 | 40 | 95 | 60 | 69 | 171 | 84 | 126 | 195 | 294 | 1,478 | 263 | 557 |
| | Self Declared | 16 | – | – | 3 | – | 1 | – | 2 | – | 2 | – | 3 | 1 | 4 | – |
| | Spammer | 55 | – | – | – | – | – | – | – | – | 1 | 3 | 22 | 6 | 18 | 5 |
| | Other | 6,851 | 10 | 7 | 263 | 273 | 302 | 231 | 320 | 252 | 462 | 480 | 692 | 1,967 | 681 | 911 |
| BotRGCN | Human | 23,137 | 29 | 27 | 1,084 | 995 | 1341 | 827 | 1092 | 863 | 1,832 | 1,459 | 2,225 | 4,648 | 2,913 | 3,802 |
| | Bot | 11,818 | 12 | 7 | 341 | 365 | 429 | 226 | 364 | 279 | 784 | 634 | 1,191 | 4,443 | 1,169 | 1,574 |

by Botometer (11,244), with those by BotRGCN (11,818), we are faced with sufficiently comparable numbers. However, compared to tweets that are instead linked to *Human* accounts, the numbers differ by no small margin (16,860 from Botometer VS 23,137 from BotRGCN). The remaining portion of tweets associated with *Human* accounts, per Botometer, must therefore be sought precisely among those accounts classified with the type *Other*. The motivation behind this statement lies in the type of approaches with which the two frameworks perform bot identification. In fact, BotRGCN does not need to query Twitter's API to make the identification, basing the latter only on the features that are passed to the model. Consequently, BotRGCN is able to classify a possible account as a bot even if in the meantime the account for which the classification is being performed has been banned, something that cannot be done with Botometer, which precisely integrates the basic information with the updated information that it retrieves from the social network. Consequently, we can assume, with some degree of confidence, that a conspicuous portion of tweets linked to real accounts were banned from Twitter in a progressively more noticeable manner as days passed during the analysis period.

Table 6 also shows that bots preferred retweeting posts rather than creating original ones. This may be because Twitter bots are often programmed to monitor specific hashtags or keywords and share relevant tweets using them. Sharing retweets is an easier and more straightforward option than creating new original tweets. Additionally, resharing posts allows bots to reduce the possibility of spamming accounts. Twitter limits the number of tweets a single account can post in a given time period to prevent spam. Bots that share more retweets than original tweets can overcome this limit and continue spreading content without being blocked by Twitter. Moreover, retweets can help increase the visibility of a bot's account, as users receive notifications when their tweets are shared and may decide to follow the bot for more content.

In general, the presence of pro-conflict propagandist bots still active is probably due to the fact that the creators of these bots have initially maximized the creation of accounts, and then developing fake profiles that appear to be genuine. Recent observations indicate that many of these bots utilize the faces of influencers from various countries to disseminate false information about the conflict[28]. Thanks to this strategy, the creators of the bots avoid the control of Twitter and create parallel identities with different political views on the conflict.

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To summarize, when analyzing the types of accounts that promote conflict, it is important to consider their behaviors in the 1st week of the conflict based on the tweets shared. As shown in Table 6, real users exhibit almost linear growth in the number of shared tweets over the days, except for March 3rd. The number of shared tweets increases daily, reaching a peak on March 2nd, which coincided with various political actions taken by different countries against Russia, probably leading to an increase in tweets to support military actions on Ukrainian territories (Fig. 3). Furthermore, the behavior concerning the number of tweets posted and shared by bots undergoes a sudden exponential growth during the last two days of the analysis period. In fact, while bots, in particular the ones classified as *Astroturf* and *Fake follower*, produce few tweets in the first few days, on the 2nd and 3rd of March, they shared a conspicuously higher number of tweets. This might be due to the creation of several bots during those days for the purpose of amplifying disinformation and immediately sharing pro-conflict tweets (See footnote 27, 28).

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[28] Source: www.bbc.com

## Analysis of public debates changes one year later

As introduced in Sect. "RU-Conflict dataset", the RU-Conflict dataset contains a large collection of tweets collected from the Streaming APIs of Twitter related to the 1st week of the conflict, i.e., from the 25th of February to the 3rd of March 2022. As we have seen in the previous analyses, different and sometimes divergent opinions have been shared by people all over the world. In this analysis, we want to investigate what are the opinions of Twitter users one year after the start of the conflict. To this end, we selected one of the most recent datasets proposed in the literature[29], namely *Ukraine Conflict Twitter Dataset* (UA dataset) [10].

Differently from RU-Conflict dataset, the UA dataset has been created using two different approaches, i.e., location- and hashtag- based approaches. The location-based approach aims to collect only tweets from Ukraine country. Instead, the hashtag-based approach involves the definition of a set of hashtags related to the conflict with the aim of extracting tweets containing these hashtags[30]. This approach is limited compared to the keywords-based approach used for RU-Conflict, since it only collects tweets with at least one of the hashtags specified in the configuration step of the crawler, and discards all others. Instead, the keyword-based approach finds a tokenized match of keywords within the body of a Tweet, extracting a larger set of tweets than the hashtag-based approach[31].

For the purposes of our analysis, we extracted tweets from the UA dataset shared between February 25 and March 3, 2023. Therefore, we evaluated 1,321,957 tweets written in 62 different languages, of which only 23,390 retweets.

*Sentiment-Analysis* Starting from the selected tweets, we conducted the sentiment analysis using *XLM-Roberta* and considering the same languages used for the analysis shown in Sect. "RQ1: To what extent do tweet sentiments vary based on either location or language?". Through this analysis, we aimed to investigate whether the sentiment distribution of tweets in 2023 differed from the sentiments expressed 1 year earlier. Figure 11 shows the statistics on the results of the sentiment analysis conducted on the tweets extracted from UA dataset. As we can see, similar to the tweets shared in 2022, there is a predominance of tweets with negative sentiment, especially in tweets written in Italian, French, Arabic, and Dutch. Furthermore, tweets with positive sentiment are always lower in number, except for tweets written in Polish where the number of tweets with positive sentiment is very similar to that with negative sentiment. As a general result, we can see a trend of sentiments very similar to that of tweets shared in 2022. However, for almost all languages analyzed the percentage of negative tweets shared in 2023 is always higher than that of 2022, except for Spanish, Hindi, Polish, Portuguese, and Russian. Instead, concerning the tweets with positive sentiments, the number of tweets is almost always greater in 2022, except for tweets in Spanish, Polish, and Russian.

*Contextual Analysis* To further investigate the content of the tweets, we conducted the context analysis using Dolly LLM and the prompts defined in Sect." RQ3: What is the perception of the Russia-Ukraine conflict in public debates on Twitter, especially those

[29] It is important to notice that, after the closure of the Twitter API in June 2023, many of the datasets available in the literature became unusable, since they contain only the identifier of the tweets and not their content, in order to comply with Twitter's Terms of Service. Thus, it was no longer possible to reconstruct (or rehydrate) the content of these tweets.

[30] www.kaggle.com

[31] Building queries for Search Tweets - www.developer.twitter.com


**Fig. 11** Percentage of tweets per sentiment shared in the 1 week of the conflict (2022) and those 1 year later (2023)

of the people most involved in the conflict?". Similar to the previous analysis, we selected tweets shared with at least one Cyrillic hashtag, focusing on tweets written in Russian and Ukrainian. Figure 12 shows the results achieved by the context analysis using Dolly. As we can see, similar to the results obtained from the analysis of the tweets in the RU-Conflict dataset (Fig. 10), the number of tweets expressing opinions in line with the promotion of messages of resistance to the actions of the conflict and those that convey the intention to end the conflict (green bars) is greater than all the others. In general, the trend in tweet content is very similar to that of tweets shared in 2022.

Concerning the tweets written in Russian with a positive response to Prompt 1, some of them continue to contain messages against the Russian government's actions despite the Russian government's propaganda restriction, while supporting Ukraine's conflict resistance actions. Furthermore, a part of these tweets, which presents positive responses to both Prompt 1 and Prompt 2, appeal to the Russian military, asking them to lay down their weapons and return home to their families. On the other hand, regarding tweets written in Ukrainian with a negative response to Prompt 1, similar to the analysis of the tweet of 2022, part of the tweets continue to express messages against the behavior of Russian citizens and governments, also asking their army to attack the Russian government. However, some of these tweets contain messages asking for the expulsion of Russians who harm civilian citizens in Ukraine in contrast to the ideals of the conflict,

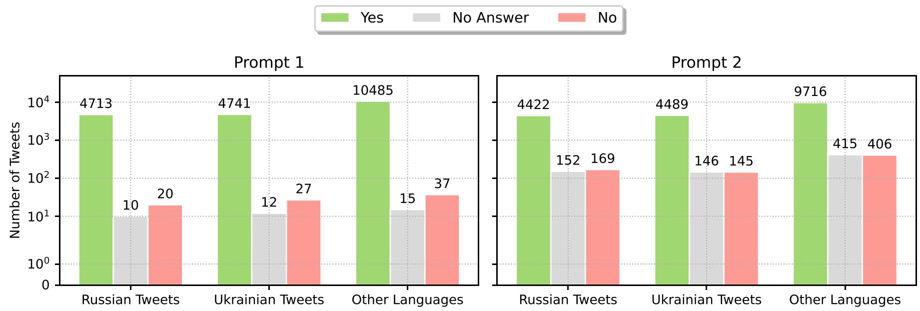


**Fig. 12** Statistics of the context-based analysis

and messages against the actions of the Ukraine government. The latter represents an interesting difference compared to the tweets of the previous year, when Ukrainians at the beginning of the war gave complete support to their government's choices. After a year, messages began to emerge that no longer supported some members and decisions of the Ukrainian government. Some examples of these tweets are shown in Table 7.

Regarding the analysis of the tweet evaluated with Prompt 2, similar to the tweets of 2022 (see Sect. "RQ3: What is the perception of the Russia-Ukraine conflict in public debates on Twitter, especially those of the people most involved in the conflict?"), there is a predominance of tweets that express the intention to cease the conflict. However, there are different tweets with a negative response to Prompt 2. In particular, the majority of Ukrainian tweets with a negative response report news on the government's choices and on the aid decided by other states. Differently from the Ukrainian tweets analyzed in RU-Conflict with the same prompt, which contain many messages expressing a feeling of anger towards the Russian government, the tweets extracted from UA dataset with a negative response for Prompt 2 mostly report news and messages of hope for the war. Concerning the tweets written in Russian, most of them with negative answers to the Prompt 2 report general news about the conflict and the attacks that occurred in different areas of Ukraine. However, different from 2022, many tweets expressed opinions about the attacks that were about to be launched against the government in Moscow and the attempted coup d'état that took place in Russia in that period. In Table 7 we report some examples of tweets extracted from the UA dataset.

In this final analysis, we have tried to investigate how the opinions in tweets on the Russia-Ukraine conflict changed from 2022 to 2023, analyzing the content of the tweets collected in UA dataset. Although the analysis is not directly comparable to that of the tweets in the RU-Conflict dataset, mainly due to the fact that the tweets available in the UA dataset were extracted with a hashtag-based strategy that is more restrictive than the one used for our dataset, we tried to investigate how public discourse on Twitter changed from one year to the next. As we expected, some of the content of the tweets has changed probably due to the influence of political developments and the ever-changing perspectives in the Russia-Ukraine conflict. This has led to a shift of a part of the public discussions towards an increased focus on geopolitical events of the other countries, and the introduction of discussion about potential threats to the Russian government, which were not considered at the beginning of the conflict.

**Table 7** Some examples of tweets extracted from the UA dataset and analyzed with the LLM

| | | Tweet | Tweet (English) | Answer |
|---|---|---|---|---|
| Prompt 1 | Ukrainian | *"сцуко, чому цих кацапських уйобків не пиздять і не викликають копів, щоб забрали російських неонацистів за напад на мирних людей? #россиястранатеррорист #россиястранаоккупант #россиястранаубийца #кацапинелюди #norussianofascism #russiaisaterroriststate"* | *"It's stupid, why don't they kick these little motherfuckers and call the cops to take away Russian neo-Nazis for attacking civilians? #россиястранатеррорист #россиястранаоккупант #россиястранаубийца #кацапинелюди #norussianofascism #russiaisaterroriststate"* | No |
| | | *"#єрмак: - пане президенте, після того як ви показали себе на прес-конференції ідіотом, який не розуміє що таке повага до людини, культура, демократія, бо вас випустили без папірця, рейтинги летять шкереберть!! #зеленський: - випускай іво бобула.. вжаримо вкраїнчиків знову!"* | *"#ermak: - Mr. President, after you showed yourself at the press conference with an idiot who does not understand that you care so much about people, culture, democracy, since you were released without a papier, the ratings will fly through the roof!! #zelensky: - let out the beans... fry the edges again!"* | No |
| | Russian | *"это было красиво! #українапереможе #slavaukraini #buenosaires #caba"* | *"This was beautiful! #ukraine can overcome #slavaukraini #buenosaires #caba"* | Yes |
| | | *"#нетвойнесукраиной #standwithukraine #путинубийца год войны... год горя, геноцида, зверств, убийств, жертв. буча, ирпень, гостомель, харьков... год безсонницы миллионов людей. год за который должен ответить путин перед трибуналом и просидеть остаток жизни в тюрьме. нет войне!"* | *"#нетвойнесукраиной #standwithukraine #путинубийца year of war... year of grief, genocide, atrocities, murders, victims. Bucha, Irpen, Gostomel, Kharkov... the year of insomnia for millions of people. a year for which Putin must answer before the tribunal and spend the rest of his life in prison. No war!"* | Yes |
| Prompt 2 | Ukrainian | *"вірте у збройні сили! разом переможемо! слава україні! #stoprussianagression #ukrainerussianwar #armukrainenow #вірювзсу "* | *"Believe in the armed forces! together we will win! Glory to Ukraine! #stoprussianagression #ukrainerussianwar #armukrainenow #вірювзсу"* | No |
| | | *"депортованих дітей-сиріт з україни змушують проходити військово-патріотичну підготовку і вчать любити росію , пишуть росгеббельсзмі. як російські фашисти старанно копіюють політику своїх дідів-нацистів! #russiaisaterroriststate #norussianofascism #смерть_фашистской_федерации"* | *"Deported orphans from Ukraine are forced to undergo military and patriotic training and are taught to love Russia, Rosgebbelszmi writes. how Russian fascists diligently copy the policy of their Nazi grandfathers! #russiaisaterroriststate #norussianofascism #death_of_the_fascist_federation"* | No |
| | Russian | *"#украина победит! империя зла падет, и все ее сатанинские последователи также будут побеждены. #putin #украина #ukrainerussiawar #россияне #ukraine"* | *"#Ukraine will win! the evil empire will fall, and all its satanic followers will also be defeated. #putin #ukraine #ukrainerussiawar #россияне #ukraine"* | No |

## Conclusion and future works

In this paper, we presented an analysis of the worldwide perception of the Russia-Ukraine conflict. In particular, we evaluated the tweets shared by the users during the first week of the conflict, since they provide a good overview of the worldwide reactions towards this new disruptive event. We have constructed a new dataset of tweets, named RU-Conflict, containing over 17 million tweets written in 63 languages, directly collected from the streaming of the Twitter platform. The dataset allowed us to perform a deep analysis trying to answer four research questions. In particular, we carried out statistical analysis on the frequencies of the hashtags used in the tweets and their correlations, as well as a sentiment analysis revealing that about the 53% of analyzed tweets turned out being negative, the 14% being neutral, and the 33% being positive. The latter are in general related to events that instill hope or, more in general, include support sentences targeted to people affected by the war. This is further supported by the contextual analysis, which highlights that most tweets convey sentiments of opposition to acts of war with messages of resistance, and a strong desire to see a resolution to the Russia-Ukraine conflict. The study also identified a significant presence of pro-conflict tweets shared by accounts that cannot be associated with real users, including over 10,000 bots. As a final result, by analyzing tweets on the Russia-Ukraine conflict 1 year later, the sentiment trends in 2023 closely resemble those in 2022. Instead, the contextual analysis revealed a shift in tweet content, which is likely influenced by political developments and evolving perspectives in the Russia-Ukraine conflict, resulting in increased discussions on geopolitical events in other countries, which were not initially considered at the conflict's onset.

The proposed study paves the way for other interesting analyses for further investigations into the impact that the Russia-Ukraine conflict keeps having on social networks. In particular, in the future it would be interesting to investigate the correlations between users exploiting single and multi-network analysis approaches, identifying communities and hidden relationships between users who shared tweets pro or against the conflict. Finally, it will be possible to provide new interesting contextual analyses by using different prompts.

**Abbreviation**

RU-Conflict Russia-Ukraine conflict

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**Author contributions**

BB: developing and testing of the analysis, methodology, Writing- Original draft preparation; LC: developing and testing of the analysis, methodology, Writing- Original draft preparation; SC: developing and testing of the algorithm, methodology, Software, Validation, Writing- Original draft preparation; VD: methodology, Writing- Original draft preparation; GP: methodology, Writing- Original draft preparation;

**Data availability**

The data used to support the findings of this study is available in the following repository: https://github.com/DastLab/RU-Conflict-Twitter-dataset.

## Declarations

**Ethics approval and consent to participate**

Not applicable.

**Consent for publication**

Not applicable.

**Competing interests**

The authors declare that they have no competing interests.

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