Empowering the Geopolitical EU in the Eastern Neighbourhood and the Western Balkans

Sentiment Analysis of the EU, U.S., Russia, China and Turkey in social media of the Western Balkans and three EaP countries

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Executive Summary

This report presents the findings of the social media sentiment analysis towards five major international actors — the European Union (EU), the United States (US), Russia, China, and Turkey — across three countries in the Western Balkans (Bosnia and Herzegovina, North Macedonia and Serbia) and three countries of Eastern Partnership (Moldova, Ukraine and Georgia). Using a Natural Language Processing (NLP)–based lexicon approach, the study processed approximately 37,000 posts from X (Twitter) and Facebook, collected between **14 February and 14 March 2025**. The collected data cover three key international events during that period: i) the speech on 14 February by JD Vance, the vice president of the US, in the 61st Security Conference that took place in Munich, Germany, ii) the meeting between president D. Trump of the US and V. Zelenskyy of Ukraine in the White House on 28 February 2025 and iii) the special European Council regarding European defence that took place on the 6 March 2025. From a methodological standpoint, this study consistently followed an innovative form of a hybrid sentimental scoring (human and automated) that provided substantial levels of reliability. In a similar vein, by analyzing two social media platforms (X and Facebook), this study served as thoroughly as possible the objective of cross- validation.

The selection of the specific dates and events was founded upon the following considerations: Firstly, from a political standpoint, the three events spawned many debates and discussions across the globe particularly as to whether relations between major geopolitical actors have reached a critical turning point. Arguably, they were followed very closely across different social media platforms, an element which increased the probabilities of intense sentimental reactions from social media users. Secondly, the three events enabled us to focus on a period of one month, something which facilitates the production of reliable data (adequate material on social media platforms, thematic variation and opportunity to detect shifts from one event to another). Thirdly, the fact that we chose three events provided the opportunity to effectively compare the sentimental dispositions towards the actors.

Overall, the empirical contribution of this report lies in the **systematic quantification of affective orientations** across multilingual datasets and multiple communication platforms. By maintaining a strict analytical consistency and minimizing interpretative bias, the findings offer a robust empirical complement to other WP3 indices such as Interdependence, Exposure Risk and Strategic Autonomy.

Across all six country studies, the results display **consistent sentiment structures and measurable cross-country variation**. Russia, the US, and the EU generated the highest frequency of references, confirming their dominant pace in public discussions in all countries or the two regions (WB and EaP). The EU generally registered the highest negative sentiment ratios; in the WB, the EU received negative dispositions on both platforms, but in the EaP countries it received positive on X. The US received consistently negative reactions in EaP

countries and mixed in the WB countries. The sentiment for Russia was overwhelmingly negative in EaP countries and more mixed in the WB countries (more favorable on Facebook). China received more positive reactions in the WB countries and more negative in the EaP countries (particularly on Facebook), whilst Turkey was the most positively viewed actor, especially on X and EaP countries. Platform-based comparison revealed that X content tended toward greater neutrality and brevity, whereas Facebook posts were longer and more emotionally polarized. Despite limitations related to translation, dataset size and time frame, the study provides a reproducible and data-driven basis for further comparative analysis.

In summing up the findings from the six countries, we can formulate the following key remarks: In **Serbia**, the EU presented consistently the most negative sentiment. The US received a rather balanced reaction (close to neutral), whilst Russia demonstrated a rather polarized outlook (strongly negative on X, clearly positive on Facebook). Both China and Turkey received very positive reactions. As regards **North Macedonia**, the EU is once more the actor that received negative dispositions on both platforms, followed by the US. Russia's outlook appeared more balanced. China received the most positive reactions, whilst Turkey a more mixed one. In the case of **Bosnia and Herzegovina**, a key finding regards the overall negativity primarily towards the EU and to a lesser extent towards the US and, on the other hand, a more neutral reaction towards Russia. China received the most positive reactions and Turkey a more mixed one. In **Moldova**, the reactions towards the EU were very positive on X but negative on Facebook. On the contrary, the US and Russia received very negative reactions on both platforms. In the case of **Ukraine**, the EU received a strongly positive sentiment on X and Facebook, whilst the US and particularly Russia, an overwhelmingly negative. Turkey also received a very positive reaction. Lastly, as regards **Georgia**, the most significant finding pertains to a generalized negative sentiment towards the EU, the US and Russia and the relatively less negative one for China and Turkey.

The findings of this report can contribute to the development of a series of policy related insights. **Firstly**, they enhance the understanding of the public perception, specifically the emotional reaction, towards the geopolitical actors both at the country level as well as the level of regions (WB and EaP). In particular, they provide a measurement of the public perception and reaction that is based on emotion rather than rational opinion. As such, the findings can be of great significance for a more comprehensive analysis of the dynamics and the impact of the geopolitical actors, particularly if they are combined with the findings of other studies, such as public opinion surveys. **Secondly**, the findings reveal concrete variations at the level of countries and the regions. In particular, they show that the EU and Russia are viewed in contrasted patterns in the WB and the EaP regions. The same is also valid for the US. This suggests that the regional framework is a crucial parameter when it comes to the favorable or unfavorable disposition towards a geopolitical actor. **Thirdly**, the findings clearly indicate the differences in the expression of public sentiment across different social media platforms. The reactions on Facebook seem to be less neutral and more polarized than X. The same counts for the shifts as regards the different reactions towards the geopolitical actors. From the standpoint of policy analysis, this is an indication that the reliance on one social media platform can be inadequate.

Inversely, the detection of recurring patterns across two social media platforms, can potentially lead to safer interpretation. Accordingly, this study offers the example of an analysis that avoids the blind spots in the monitoring of the perceptions, and specifically, the sentiments towards geopolitics.

Keywords: sentiment analysis, social media, geopolitical actors, Western Balkans, Eastern Partnership, Natural Language Processing (NLP), monitoring of public sentiment, sentiment dynamic

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List of Abbreviations

Apify- online platform for web scraping
BBC- British Broadcasting Corporation
BiH- Bosnia and Herzegovina
CSV- Comma-Separated Values
DeepL- platform for automated translation
EaP- Eastern Partnership
EU- European Union
NATO- North Atlantic Treaty Organization
NLP- Natural Language Processing
R- Programming Language and Environment for Statistical Analysis
RStudio- Environment for the application of the tools pertaining to R methodologies
URL- Uniform Resource Locator
US- United States
VADER- Valence Aware Dictionary and Sentiment Reasoner
WB- Western Balkans
WP3- Work Package 3
X- Social media platform (formerly Twitter)

Introduction

This report presents the findings of the social media sentiment analysis within an empirical framework that assesses the geopolitical competition between the EU and actors such as the US, Russia, China and Turkey, in the Western Balkans and the Eastern Neighbourhood. It consists of a systematic and quantitative assessment on the affective dispositions (positive, negative and neutral) of a part of social media users in WB and EaP countries towards the five actors, EU, US, Russia, China and Turkey.

Thus, the outcome of the sentiment analysis can be regarded as an additional index, one that informs on the dynamics and the equilibrium between the actors when it comes to affective reactions from the citizens who are active on social media. In the case of the **Strategic Autonomy Index**, which focuses on the perception in the different WB and EaP countries when it comes to the EU's autonomy as an actor, sentiment analysis can provide an indicator that complements the understanding by adding an extra layer of measurement. The most immediate contribution is the estimation of the alignment and the correspondence of the data compiled in the three indices (Interdependence, Exposure and Strategic Autonomy) with those of the sentiment analysis. In particular, this entails the exploration of whether and how exactly a high or medium degree of interdependence or exposure is evident or detectable in the affective dispositions of the social media users, as part of the general public. The measurement provided by the sentiment analysis stems from a specific and limited part of the general public (social media users of two platforms, X and Facebook during a specific period). In other words, no claim of universality or general applicability cannot be put forward as regards the findings. Nonetheless, due to a thorough analytical scheme, the findings provide solid indications that should be taken into account.

Sentiment analysis (a quantitative methodology based on NLP- Natural Language Processing) is already used as an additional tool to explore the public or the citizens' dispositions and reactions to political actors and their policies in the national or international field (Fisher et al. 2022). It has become a valuable tool for political science, economics and marketing, sociology and communication (Wankhade et al. 2022; Islam et al. 2020). Its usefulness can be linked with the specific conditions of contemporary societies, especially from a communicative perspective: interconnection of national and international public spheres, big data, steady growth of social media, spread of disinformation and fake news. In effect, the EU has introduced its own concept to refer to this unstable climate that affects public communication and ultimately politics; by referring to 'manipulated information', the EU includes the aspects of propaganda, disinformation and 'fake news' (Bentzen 2017; Bleyer-Simon 2025). Within this framework, sentiment analysis can provide quantifiable insights (i.e. sentiment scores) across sizable datasets. Such measurements ought to be thought as indicators that could render more visible the shifts of affective dispositions of the general public, the differentiations within the public itself according to different channels of communication (social media platforms). It can also provide insights as regards the effects of manipulated information (i.e. frequency, form and potential outcome). As it applies to all methodologies, the pertinence and the validity of sentiment analysis should be constantly scrutinized. By this process, its input can be taken into account not necessarily as definite proof but rather as a shortcut that makes big data more accessible to reflection and a more systematic understanding.

Analytical framework and rationale

The purpose of the social media sentiment analysis within the GEO- Power- EU project was the measurement of sentiment scoring regarding five actors (EU, US, Russia, China and Turkey), in 6 countries (Serbia, Bosnia and Herzegovina, North Macedonia, Ukraine, Moldova and Georgia). In order to produce the relevant data in a consistent manner for all countries, research design focused on the study of the same time period- and events- across two social media platforms (X and Facebook) in six different countries (three Western Balkan countries: Serbia, Bosnia and Herzegovina, North Macedonia and three EaP countries: Moldova, Ukraine and Georgia). It was a challenging task, since it dealt with six different countries and languages and furthermore with six distinct contexts of social media use. The research was conducted within the period of October 2024 until October 2025. The first phase (autumn 2024 to late spring 2025) consisted of a pilot study- aiming at fine-tuning the research design- regarding the elections in Georgia in October 2024. The second phase (summer 2025) concentrated on the collection of social media posts related to the events that took place in Spring of 2025 and their analysis. The third phase (October 2025) was dedicated to the preparation of the final report.

The study covers the period between 14 February and 14 March 2025 and it focuses on three events that had significant repercussions in the evolving dynamics of geopolitics: i) the speech on 14 February by JD Vance, the vice president of the US, in the 61st Munich Security Conference, ii) the meeting between president D. Trump of the US and V. Zelenskyy of Ukraine in the White House on 28 February 2025 and iii) the special European Council regarding European defence that took place on the 6 March 2025. The first events were selected as turning points in the EU- US relations and partnership (more generally the so-called 'Atlanticism') and the US- Russia relations and their impact on the war in Ukraine. The third event was selected as the landmark of new EU defence policies that were speeded up with decoupling of the US and EU in foreign and security matters. In effect, both the JD Vance speech and the Trump- Zelenskyy meeting were interpreted as a critical test for the cohesion and the quality of EU-US relations and the resilience of their shared objectives and values. The attack of JD Vance on EU precisely with regard to the quality of the democracy that the latter promotes (i.e. the reference to the risk of tyranny over Europe or the idea that a bigger threat to Europe comes from within and not Russia or China) cast a doubt as to the extent to which the two sides perceive these matters in the same way. The rhetorical construction and the framing of these issues by JD Vance revealed a logic of simplistic confrontation ('Us' vs 'Them') in which it was not clear what is the position assigned to the EU (Tomala 2025). In a similar vein, the dramatic and confrontational outcome of the meeting between presidents Trump and Zelenskyy also raised questions as to whether the US will pursue a more unilateral approach (direct bilateral negotiations with Ukraine and Russia and not multilateral) as regards Ukraine, something which will possibly weaken its own position (Jakupec 2025). In this tense climate, in which one should also take into account president Trump's suggestions about the need to reform NATO, the EU leaders held a special

Council on defence, aimed extensively at upgrading the EU's defence and military capabilities (De Rakt & Kefferputz 2025).

It is important to clarify that our social media sentiment analysis deals exclusively with affective dispositions towards the actors and not necessarily a specific policy or dimension of these events. The selection of these three events has a number of advantages The first advantage is that they were followed extensively at the international level and provoked discussions and reactions at the national level, and in particular across different social media platforms, like X, Facebook or Instagram among others. This aspect raised the possibility of collecting a sufficient amount of data for analysis. Secondly, it was a compact period (1 month) with little temporal distance from event to event. Presumably, this enabled the capturing of the spontaneous expression of sentiments from event to event, much more than if the events were separated by longer interval periods. The third advantage was the possibility to collect extensive or sufficient amounts of data on key GEO-POWER-EU actors: the EU, US and Russia that were of great interest to our study.

On the other hand, there are also challenges and limitations. Firstly, the length of the period does not easily permit the formulation of more general remarks and conclusions about enduring sentiments towards the actors but rather the sentiments in relation to the specific period and events. The period is certainly more significant than a single event with a few days (i.e. one week) for study but is also less reliable for a measurement of long-standing trends that could be produced with a study of a six-month or a twelve-month period. Secondly, the period and the events chosen are not directly linked with actors such as China and Turkey and thus one might expect less relevant data for them. However, the studies also give us the opportunity to obtain a measure- for all actors- with regard to their frequency as objects of reference. Thirdly, the selection of events inevitably influences the affective dispositions. Nonetheless, this study commits itself to extracting the sentiment towards the actors without any interpretation of either the political, historical or cultural context of the country.

Methodology

The methodological component of this study was designed specifically so that it satisfies a major research objective: the quantification of public affective dispositions towards five actors (EU, US, Russia, China and Turkey) in six countries (Western Balkans: Serbia, Bosnia and Herzegovina and North Macedonia and Eastern Partnership: Moldova, Ukraine and Georgia). The methodological paradigm followed can be summed up as a quantitative, lexicon- based sentiment analysis with limited qualitative interpretation (lexicometry). As such it falls under the general category of Natural Language Processing (NLP) which enables the processing of large volumes of data from social media content. By sentiment, we employ the classification of distinguishable units of data according to three main categories: positive, negative and neutral. It is important to clarify that the analysis was not solely based on computational and automated tools. Our approach could be described as hybrid, given that a very important part of the data was also scored manually in an effort to cross- validate and drastically improve sentiment analysis through R.

In general, the textual data can be analyzed and classified according to different levels: the document (i.e. entire article, entire post), the sentence (an autonomous unit of meaning within a text) and the multimodal level (i.e. combination of textual, visual and audio elements) (Wankhade et al. 2022; Chaturvedi et al. 2018). In our case, the focus is on textual data, in particular X tweets and Facebook posts. We focused on the sentence as a unit of analysis and not the text of an X tweet or a Facebook post in its entirety, given that a tweet or post may contain several sentences and also that a single sentence may contain references to more than one actor. Thus, we chose to delimitate our analysis on references to the actors within the confines of a sentence. In other words, a sentence containing more than one reference to the actors was analyzed more than once.

Our approach is founded upon the use of appropriate lexicons and packages and in this respect it falls under the core NLP paradigm. We employed RStudio which is an integrated environment for programming and the use of different packages and scripts that enable the processing of data. In terms of lexicon and packages, we employed Sentimentr, which is an equivalent of VADER (Valence Aware Dictionary and Sentiment Reasoner) and Syuzhet, which is an equivalent of Text Blob (package for sentiment analysis), in an effort to cross-validate the sentiment scoring and produce an optimal score as an aggregate. This choice served the purpose of addressing some of the main challenges and difficulties that regard a lexicon-based sentiment analysis. **Firstly**, we refer to the **distinction between factual statements and opinion**. This task is definitely more complex in bigger texts that by definition blend factual data and opinion (a statement or discourse by politicians, an op-ed). In our case, the social media posts are by definition oriented towards the interpretative and affective pole and not the factual or that of information. In this regard, we also had to deal with misclassification in relation to all events.

For instance, on the occasion of the JD Vance speech in the Munich Conference, many social media users merely reproduced the part of his speech where he mentioned that the biggest threat to Europe's security comes 'from within', and not from Russia or China. Due to our aggregate scoring, we detected that this was a typical example of differentiated scoring (i.e. neutral for all actors, EU, Russia and China or negative for EU and neutral for Russia and China). Another example was the information that US and Russia would meet (18 February 2025) in Saudi Arabia to find ways to end the war and bring peace in Ukraine (neutral for US and Russia, positive for US and Russia). Such examples were not rare but certainly they were not dominant in terms of percentage.

Secondly, a major challenge regards **the handling of sarcasm and irony**. In particular, in some countries we encountered a frequent use of terms that were not- and in all probability could not be- recognized by the lexicons in their full affective relevance. Such was the term 'Putler', a neologism that associates Russian president V. Putin to the leader of Nazi Germany, A. Hitler. In many cases, when the use of the term was not necessarily associated with other negatively charged terms, it was classified as neutral. However, due to the fact that we were able to detect it in the early stages we were able to rectify it on the basis of human scoring.

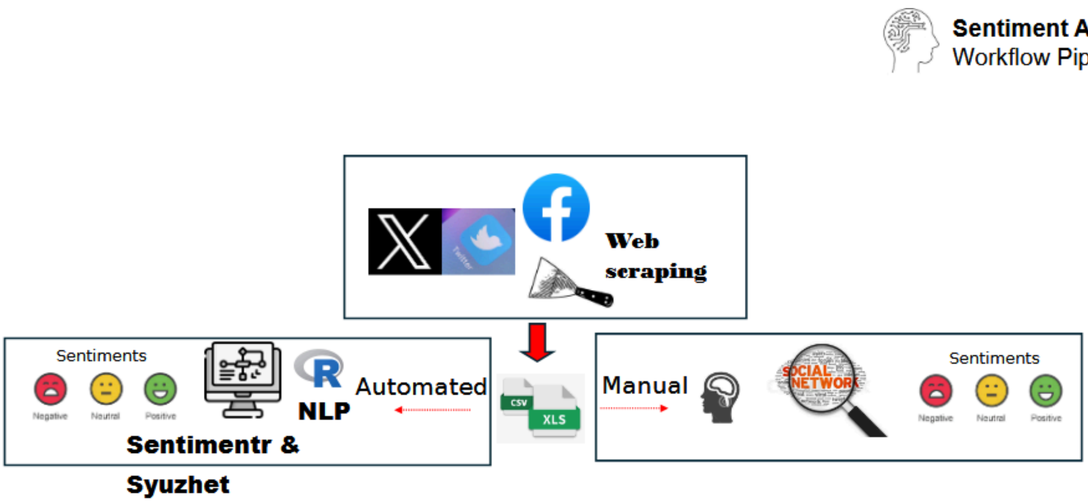
Of course, there are many more subtle examples. For instance, we may refer to a phrase such as 'Russia wants peace for Ukraine. Really?'. In several cases, such sentences were classified differently by the different lexicon and packages (i.e Positive for Russia, Neutral for Russia, Negative for Russia). A common outcome for such cases was the neutral classification. A **third important challenge** relates to **the different social, cultural and historical context** of the countries. In this regard, we did encounter content that did have affective aspects not detected by the lexicons. For instance, in the case of Serbia there were several references to the actions of the US in 1999 (evidently referring to the war in Kosovo). In Georgia, similar references regarded Russia's actions in the war of 2008). Such content obtained differentiated classifications only in cases where the references were short and void of any other elements. In all countries we encountered such examples. Although we cannot provide the exact rate of their frequency, on the basis of the differentiated scoring, we can confirm that they were not very frequent.

A **fourth significant challenge** was the **multilingual nature** of the datasets that we had to analyze. Our sample consisted of six different languages, whilst the lexicons and the packages for sentiment analysis that we used are designed to handle text in the English language. Therefore, we had implemented the procedure of translation of the social media content from the original language to English using available tools (DeepL and Google Translate). The translation was verified by the partners in the GEO-Power-EU project. We cannot measure the loss of accuracy in the process of automated translation. Still, we aimed at applying the optimal procedure in order to be in a position to implement the sentiment analysis according to its design.

A hybrid form of sentiment scoring was designed, one that combined computation with corroboration from a human coder. Once the full sample was collected and translated for all six countries and thus ready for the sentiment scoring, we extracted the half of the total sample and applied both types of scoring on the same sample, one that is done by one human coder and a second one performed via computation on the basis of the script that we developed for R. By this process we obtained a mean agreement in all cases of almost 50% (the highest was for Ukraine, 57%). This validation enabled us to retain the part of the sample for which there was an agreement and corrected the disagreements.

When this correction was completed, we proceeded to the scoring of the second half of the sample, by following a reversed course. In this case, the first scoring was provided by computation and the human coder applied corrections when necessary. Subsequently, the sentiment analysis we performed did not rely entirely on automation and computation. Rather, the NLP component was used both for cross-validation of human coding and also for speeding up the process of sentiment scoring, but still under the supervision of human coding. Given that the mean agreement was at the level of 50%, we estimate that with the subsequent corrections, there was a considerable improvement of the sentiment scoring, something which certainly maximised the validity and the reliability of the analysis and the production of meaningful empirical data. The following figure contains a schematic presentation of the hybrid approach that we employed.

Figure 1. Schematic outline of the analytical framework



In recent times and in light of the growing interest to analyze big data, particularly social media content, one finds numerous studies that perform lexicon-based sentiment analysis, including R packages such as ‘sentimentr’ and ‘syuzhet’. Certainly, there is a consensus that there are important limitations when it comes to the accuracy of the lexicons and thus a caution against an unrestricted reliance on the computational approach (Kim 2022). The application of such packages does seem to yield promising results, however their effectiveness also depends on the type of data as well as the analytical scope. For instance, it is likely that the lexicons are overwhelmingly reliable and accurate (above 90%) with regard to datasets such as customer reviews or the evaluation of services in general (Mahmoudi et al. 2024). Naturally, these packages have been applied to many different datasets, including literary texts such as novels, political speeches, media texts or even interviews. Social media content has also been studied in similar ways. The specificity and the difficulty of our endeavor lies in the fact that we were interested in extracting sentiment for five different objects of reference (the actors: EU, US, Russia, China and Turkey), within the confines of small textual units (X tweets and Facebook posts).

In other words, the existing literature tends to support the hypothesis that NLP and the corresponding packages will perform more effectively with regard to one or rather very few objects of reference (i..e one politician in connection to one or two topics, the customers in relation to one service of a given provider, social media users in relation to one actor or topic and so on). Thus, the decision to use NLP in a hybrid scheme of analysis appears to be in correspondence with the premises of sentiment analysis through NLP and appropriate lexicons. In the following parts of this chapter we present the various stages of the methodological instrument, namely data collection, data processing, data analysis and data interpretation.

Data Collection

The data collection began with the decision to focus primarily on X and also Facebook in all six countries. The platform X was chosen due to the fact that it is commonly used for real-time commentary and in a form (small text) that is very suitable for grouping many comparable units of analysis (tweets) and also for transforming texts into numerical values for the application of the lexicon. Facebook is also a platform that favors real-time commentary in a textual form. Our social media sentiment analysis does not claim that its findings have a general applicability as regards the wider public or all social media users. Our findings relate first and foremost to the specific sample, the events and the period chosen for analysis and they provide indications that point at- not necessarily validate or prove- possible trends. This precaution stems from the awareness that the social media users form only a portion and a specific expression of the public opinion and the general public in a given country.

Initially, the objective was to focus solely on X. Arguably, X is a platform that, albeit a much more limited share of users compared to Facebook or Instagram, is likely to favor political commentaries and reactions from parts of the audience that follow closely national and international news. In effect, it has been suggested that users who publish content on X are more prone to engage in discussions and debates on politics (McClain et al. 2024). However, we also had to take into account the fact that Facebook is far more popular than X at a global level and especially in the countries under study (see Table 1). Undoubtedly, political debates and discussions are also present in Facebook but they seem to follow a different logic. X is linked with real-time political analysis, whilst in Facebook, political analysis takes place within broader and more diversified social frameworks and networks (Boulianne et al. 2024). Subsequently, the decision was made to add Facebook as a second platform not for the entire period but only one of the three events, the meeting between presidents Trump and Zelenskyy at the White House. Only in the case of Bosnia and Herzegovina, there was a consensus to focus primarily on Facebook and secondarily on X; this choice was motivated by the systematic observation of the rather poor results on X in the context of preliminary searches. Therefore, our determination to simultaneously include X and Facebook was driven by the aim to take into consideration and juxtapose two different versions of political analysis and commentary. This choice served a rationale of exploration and empirical abundance rather than comparison based on representativity.

Table 1. The use of social media platforms in the countries under study (Compiled with data available World Population Review.)

Country (Population)	**X users (% of population)**	**Facebook users (% of population)**
Serbia (6.7 M)	677.8 K (10%)	4.8 M (71%)
Bosnia and Herzegovina (3.1 M)	161.2 K (5%)	2.0 M (64%)
North Macedonia (1.8 M)	125 K (7%)	1.4 M (77%)

Ukraine (39 M)	1.5 M (4%)	20.6 M (53%)
Georgia (3.8 M)	216.3 K (6%)	3.7 M (95%)
Moldova (3.0 M)	144.3 K (5%)	1.9 M (63%)

Another important aspect of the data collection was the preparation of a series of **hashtags** to facilitate the social media scraping. Indisputably, since the emergence of Twitter (now X), hashtags have played a key- almost structural- role when it comes to facilitating the topical categorization and thematic navigation of users (as publishers or readers of content) through many different and ever-evolving stories. Progressively, hashtags became impactful tools in the realms of political and more generally strategic communication, since they often act as frames- patterns of interpretation- that orient the understanding of a topic towards a specific direction (Hemphill et al. 2013). However, the growing reliance on algorithmic criteria for visibility and navigation (i.e. a user's networks, past interactions and interests) have somewhat limited the function of hashtags as main drivers for content discovery and interaction (Bucher 2018). Hashtags are very much present but not as a structural dimension that determines the production, the distribution and the interaction with a given content. Therefore, our conclusion was that hashtags could be exploited as means of detecting relevant content, but not with a view to limiting our analysis on the content retrieved through them. In other words, we employed both hashtags and other search terms relevant to the events that we studied in order to maximise the data collection and amplify the relevant dataset. For instance, if for the first event (the speech by US vice president JD Vance) we focused solely on relevant hashtags (i.e. #VanceMunich), there was the risk of not including very relevant content published without the use of the hashtag. To respond to this challenge, we used several combinations of different search terms (i.e. hashtags and terms relevant to the event) in order to retrieve as much of the pertinent content as possible.

In the end, nearly 37.000 X tweets were collected and analyzed for all countries. In the case of Facebook, the procedure was slightly different. The collection was also enabled by using the relevant hashtags as search terms, but the search was focused on a **pre-determined list of news media and blogs t**hat were active on Facebook and published posts relating to the three events. In essence, we identified comprehensive lists with such news media and detected the relevant posts. By using the appropriate tools for scraping we collected all the comments and the replies of the Facebook users to the initial post. By this procedure we managed to collect an ample sample of Facebook posts. The scraping of social media content was done by using the platform *Apify* (https://apify.com/): , one for X: **Twitter (X.com) Scraper Unlimited (Apify)** – used for collecting tweets (X data) and one for Facebook: **Facebook Posts Scraper (Apify)** – used for collecting Facebook posts.

For both cases, we were very careful to apply strict criteria for geolocation, safeguarding that the results obtained will refer to **social media users residing in the respective country**. By this approach, we may have narrowed the results obtained but we certainly gained on the homogeneity of the sample, which was an essential element for a study in different countries. The collected data were obtained in the form of Microsoft Excel or Csv files. Each X tweet and Facebook post was accompanied with a series of data, which were the following, among many others: user id, location, author description, number of likes, number of followers, number of retweets, post url and so on. The sentiment analysis adhered to strict ethical principles to ensure the responsible treatment of social media data across all six countries and both platforms (X and Facebook). First, **only publicly available posts were collected and analyzed**. This means that the dataset included *exclusively content that users had intentionally made public*; no private accounts, restricted posts, or closed-group discussions were accessed. This approach aligns with widely accepted standards for observational research in digital environments, where publicly accessible content is considered permissible for academic analysis without infringing on user privacy.

Second, **all datasets underwent a comprehensive anonymization process prior to analysis**. This involved removing any identifying information associated with the posts, including user IDs, usernames, profile descriptions, URLs that could lead back to the original content, and any metadata that could enable the re-identification of individuals. As a result, the analytical corpus contained only the textual content required for sentiment scoring, completely decoupled from personal identifiers. This ensured that none of the analyzed material could be traced back to specific individuals. This anonymization procedure was applied **systematically and consistently across all countries and both social media platforms**, following the same protocol to guarantee methodological uniformity and ethical integrity throughout the study. By limiting the dataset to public posts and eliminating all personal identifiers, the study minimized potential risks to individuals while maintaining compliance with ethical guidelines for research involving digital trace data.

Data processing

This stage was also very demanding in light of the fact that we had to replicate it with consistency across six different countries. The first step was the translation of the datasets per event, given that in all cases the scraping regarded a specific timeframe corresponding to each event and sub-period: i) for the JD Vance speech it was from 14 February to 27 February, for the meeting between Trump and Zelenskyy it was from 28 February to 5 March and for the EU Council on defence it was from 6 March to 14 March. For the cases of Serbia, North Macedonia, Bosnia and Herzegovina and Georgia we employed Google Translate and for the cases of Moldova and Ukraine we employed DeepL.

Once the translation was completed, the second step regarded the extraction of 5 distinct sub-corpora (each for every one of the 5 actors: EU, US, Russia, China and Turkey) that contained the sum of all the sentences with references to the actors. This was a step with enormous repercussions on the nature of the sentiment analysis that we performed. Of course, the EU differs from the other actors in the sense that it is a very specific type of supra-national organization that encompasses very powerful and impactful actors such as France and Germany, among others. However, our study captured only the explicit references to the EU. The results might have been different if we included references to countries such as Germany, France or even Italy and Poland. On the other hand, it was equally challenging to measure the presence of the EU in itself. It is important to clarify that the sentiment analysis for each actor regarded only the relevant sub- corpus. We did not apply it in an indiscriminate fashion on a specific hashtag or a specific set of results retrieved by a search with various terms. All the results per event were firstly combined. This provided us the opportunity, firstly, to remove tweets or posts that were collected more than once and, secondly, to re-organize the data into 5 specific sub- corpora.

Table 2. The terms used to search for content relevant for strategic actors

Strategic Actor	The Terms used to search for content related to the strategic actors
EU	EU, Europe, European, Brussels, European Union
The U.S.	US, USA, Trump, White House, Washington, America, American
Russia	Russia, Russian, Kremlin, Putin and Moscow
China	China, Chinese, Xi Jinping and Beijing
Turkey	Turkey, Turkish, Erdogan and Ankara

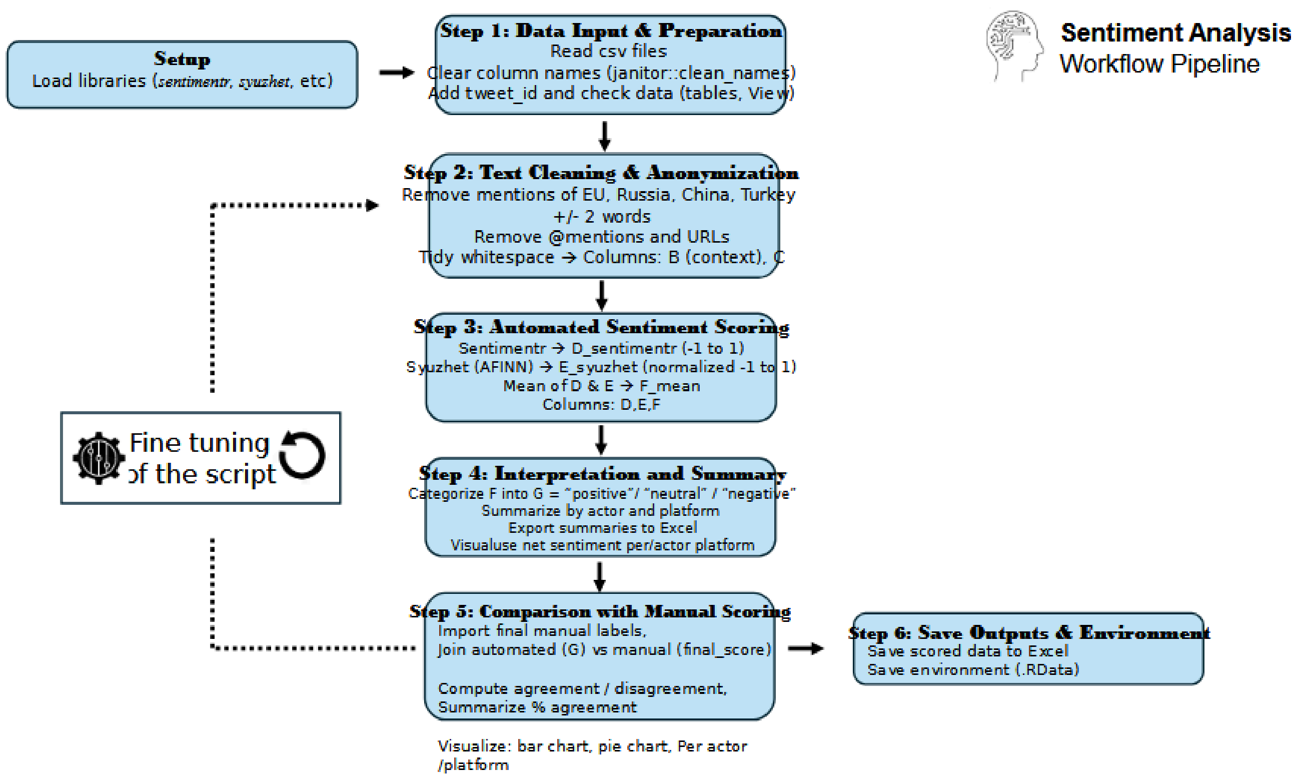
The fact that we applied this procedure on the already translated dataset facilitated a consistent and uniform treatment in all cases. This process was implemented in the environment of RStudio where we used the libraries 'tidyverse' and 'tidytext'. The third step of data processing, always in the pre-analysis phase, regarded the cleaning of the data, the sub-corpora, from stop words such as articles, pronouns and prepositions as well as the elimination of urls, emojis and duplicates. This was also implemented in R with the libraries 'tidyverse' and 'tidytext'.

Data Analysis

On the basis of the steps followed in the module of data processing and prior to the application of the sentiment analysis, we had obtained in total the number of 20 Csv files, which corresponded to the actors' subcorpora per event (i.e. five for event 1.: JD Vance speech on X, five for event 2.: Trump-Zelenskyy meeting on X, five for event 3.: the EU Council on Defence on X and five for event 2. Trump- Zelenskyy meeting on Facebook). Subsequently, we proceeded to the manual scoring of about half of the total amount of tweets and posts included in these files. Once the manual scoring was concluded, we then proceeded with the automated scoring of the exact same sample on the basis of the script that we designed for R.

The version that ran in all cases included the following stages: **1. The setup** which essentially consisted in making sure that both libraries/ lexicons (sentimentr and syuzhet) are operational, **2. The data input and the preparation**: in all cases we chose the csv file format; we also added a tweet id. **3. The text cleaning and anonymization**: this is a procedure of crucial importance since it involved the removal of URLs and user ids (i.e. @) and also the removal of references (+/-2 words) to the actors that were not supposed to be scored. For instance, if a dataset regarded the scoring of the US, then the script removed mentions of EU, Russia, China and Turkey (as they were defined previously, i.e. EU= Europe, European, Brussels and so on). In particular, we opted for the removal of a minimum of the two words preceding and succeeding the actors not to be scored, in an effort to retain the most relevant content for the actor to be scored. **4. Automated sentiment scoring**: the logic entailed the separate application of a score by sentimentr (column d, -1 to 1) and another one by syuzhet (column e, -1 to 1). In a separate column (F) we obtained the mean between the two scores, which we would later use for determining the agreement. **5. Interpretation and summary**: in this step, we transformed the scoring from numerical to a descriptive label (positive, neutral and negative) and also summarized the results by actor and platform; the scored datasets are exported to Excel sheets. **6. Comparison with manual scoring**: essentially we combined the two datasets and we computed the agreement and disagreement by summarizing in %. **7. Saving of outputs as well as the environment.** The following figure illustrates the succession of the different steps.

Figure 2. The successive steps of the R script for the automated sentiment scoring



As it was mentioned, in all countries we were able to obtain a mean agreement of 50% between the manual and the automated scoring. This was a fundamental steppingstone that facilitated both the cross-validation of an important part of the sample as well as a swifter correction and improvement of the sample that fell into the categories of disagreements. The following figures illustrate the percentage of agreement and disagreement for Ukraine as well as the distribution of agreements and disagreements per sentiment category (negative, positive and neutral). It is noteworthy that the biggest percentage of disagreement is found in the neutral category (70%). This is directly linked to the fact that most commonly we detected in this category the X tweets and the Facebook posts that contained multiple references to more than one actor (references to two actors and sometimes three actors). From this standpoint, the human assessment was quintessential for sorting which part of the tweet or post contained the relevant content that revealed sentimental patterns towards a specific actor.

Figure 3. The percentages of agreement and disagreement as regards the sample from Ukraine between the manual and the automated scoring.

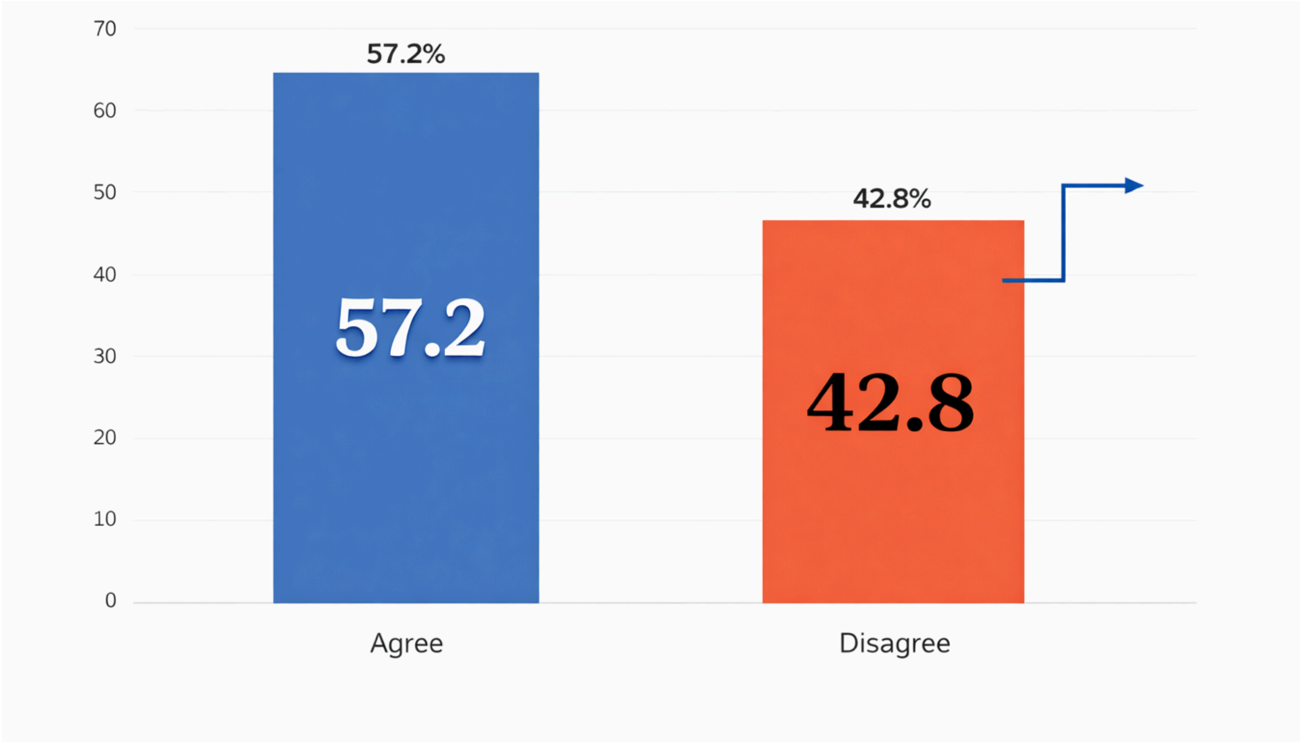


Figure 4. The distribution of agreements and disagreements per sentiment as regards the sample from Ukraine between the manual and automated scoring.

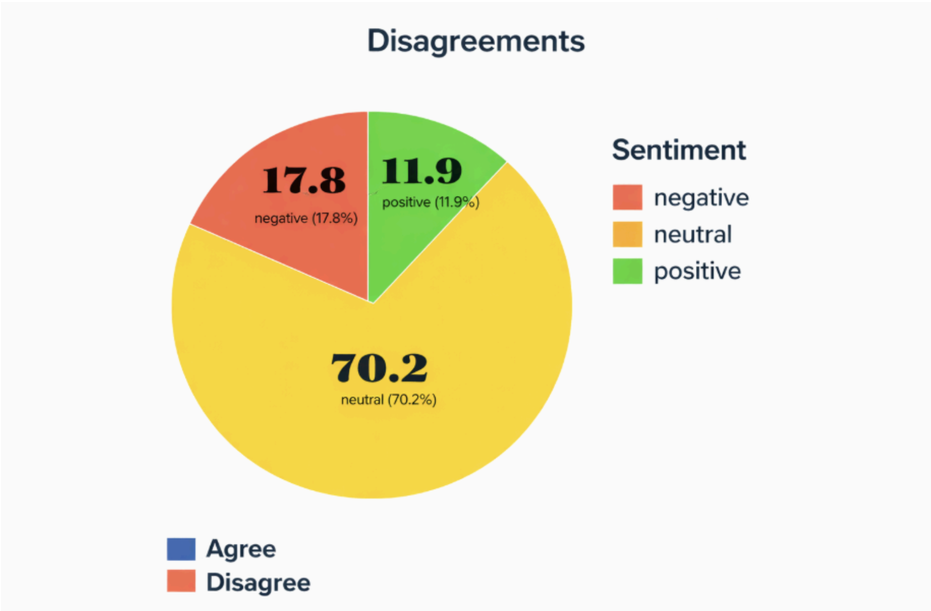


Table 3. Example of the joint file for assessing agreements and disagreements of the manual and automated scoring (the analyzed data are of the sample from Ukraine)

Post id	Original post	Post after words removal	Anonymized post	Actor	Platform	Country/ post origin	Sentimentr score	Syuzhet score	Mean (auto score)	Auto score	Human score	Agreement
3	@...Russia is a killer of Ukrainian people…	@...Russia is a killer of Ukrainian people…	Russia is a killer of Ukrainian people…	Russia	X	Ukraine	-0,10 …	-0.8	-0.45	Negative	Negative	Agree
4	@...Meanwhile, Russia is spending billions of euros to manufacture weapons and pay its citizens to kill Ukrainians.	@...Meanwhile, Russia is spending billions of euros to manufacture weapons and pay its citizens to kill Ukrainians.	Meanwhile, Russia is spending billions of euros to manufacture weapons and pay its citizens to kill Ukrainians.	Russia	X	Ukraine	-0,12 ..	-0.8..	-0.46	Negative	Negative	Agree
5	@...Yeah. we are everything and everywhere and everyone, but Russia - don't … up	@...Yeah. we are everything and everywhere and everyone, but Russia - don't … up	Yeah. we are everything and everywhere and everyone, but Russia - don't … up	Russia	X	Ukraine	0	0.2	0.1	Neutral	Neutral	Agree
6	@... Fool, Russia will go along with China, and he has	@... Fool, Russia will go along with China,	Fool, Russia will go along with China, and he has already set up his military	Russia	X	Ukraine	-0.4	0	-0.2	Neutral	Neutral	Agree

	already set up his military facilities in Europe.	and he has already set up his military facilities	facilities									
7	Rubio: We need to see if Russia is serious about ending the war	Rubio: We need to see if Russia is serious about ending the war	Rubio: We need to see if Russia is serious about ending the war	Rus sia	X	Ukrai ne	-0.13	-0.4	-0.2 6	Neutra l	Neutr al	Agree
8	Audience shocked by US vice president's speech in Munich - BBC De Vance criticised Europe, not Russia	Audience shocked president' s speech in Munich - BBC De Vance criticised	Audience shocked president's speech in Munich - BBC De Vance criticised	Rus sia	X	Ukrai ne	-0.22	-0.4	-0.3 1	Neutra l	Neutr al	Agree
9	Russia can "very quickly" destroy Ukrainian cities by 100%, including Kyiv, but does not want to do so;	Russia can "very quickly" destroy Ukrainian cities by 100%, including Kyiv, but does not want to do so;	Russia can "very quickly" destroy Ukrainian cities by 100%, including Kyiv, but does not want to do so;	Rus sia	X	Ukrai ne	0.13	-0.4	-0.1 3	Neutra l	Negati ve	Disag ree

As it is illustrated in the table, the signalling of the disagreements with a different color enables the human evaluator to focus directly on the score that needs revisions. Certainly, we do not claim that by this configuration we achieved a perfect scoring, something which by definition appears to be very challenging to achieve. The subsequent set of results produced for every case was the assessment of the different affective categories that could be detected in the subcorpora of the actors. This procedure can be regarded as exploratory. We decided to include it as a means to provide a more qualitative view on the data always within the empirical aspect and not by interpreting them -in the context of the sentiment analysis- with other contextual and country specific elements. One may describe this aspect as an extraction of sentiment families and it was founded upon the premises of lexicometry. In effect, we established three main affective categories (positive, neutral and negative), all of which were divided into smaller units corresponding to different types of emotions. By using the relevant libraries in R (‘tidyverse’, ‘stringr’,’readr’), we created and expanded pre-determined lists with terms that relate to each of the sentiment categories. For instance, the positive, neutral and negative categories included the following options:

Positive categories

- Trust = c ("trust", "reliable", "honest", "dependable", "faith", "loyal", "transparent", "integrity", "truthful", "credible"),
- Status = c ("admire", “power”, "respect", "praise", "leader", "strong", "great", "inspiring", "courageous", "role model", "commend"),
- Similarity = c("shared", "aligned", "similar", "joint", "common", "united", "mutual", "close", "connected", "like-minded"),
- Expectations = c("cooperate", "support", "help", "aid", "ally", "assist", "partnership", "work together", "back", "collaborate"),
- Hope_Optimism = c("hope", "progress", "future", "believe", "optimistic", "improve", "bright", "potential", "aspire", "moving forward"),
- Security = c("secure", "safety", "protection", "stable", "peace", "defense", "order", "calm", "shield", "reliable environment")

Negative categories

- Distrust = c("lie", "fake", "untrustworthy", "corrupt", "deceive", "dishonest", "fraud", "mislead", "cover-up", "crooked")
- Betrayal = c("betray", "traitor", "backstab", "treason", "sold out", "disloyal", "turn against", "double-cross", "abandon", "stabbed"),
- Hostility = c("hate", "violence", "attack", "enemy", "aggression", "threat", "war", "bomb", "assault", "rage"),
- Difference = c("different", "foreign", "incompatible", "alien", "opposing", "clash", "conflicting", "separate", "distinct", "divergent"),
- Manipulation = c("propaganda", "manipulate", "exploit", "brainwash", "deceit", "influence", "twist", "control", "agenda", "coerce"),
- Fear_Insecurity = c("fear", "danger", "unstable", "chaos", "insecure", "panic", "threat", "worry", "terror", "collapse")

Neutral categories

- Observation = c("said", "noted", "reported", "stated", "mentioned", "claimed", "declared", "observed", "added", "commented"),
- Complexity = c("complex", "mixed", "nuanced", "depends", "uncertain", "ambiguous", "complicated", "conditional"),

- Indifference = c("indifferent", "irrelevant", "who cares", "doesn't matter", "whatever", "don't mind", "unconcerned", "neutral"),
- Uncertainty = c("maybe", "unclear", "unsure", "doubt", "possibly", "uncertain", "not sure", "could be", "perhaps", "ambiguous"),
- Dissociation = c("stay away", "not involved", "distance", "detached", "separate", "uninvolved", "disengaged", "neutral", "aloof", "apart")

This procedure was designed to be as consistent as possible and in full alignment with the sentiment scoring. In essence, we created a csv file per actor that contained the overall sentiment score for the whole period. Afterwards, we attempted to detect by means of a lexicometric approach the positive sentiment family within the positively scored data; the same focus was maintained for the neutral and the negative. This process yielded results worthy of attention; however, we ought to state emphatically that this procedure lacked the cross-validation used for the sentiment analysis; its character is mainly heuristic and exploratory and thus we abstained from providing statistical data but rather general indications of frequency.

Data Interpretation

As it was already mentioned, the primary objective of the sentiment analysis was to focus on empirical research and provide verifiable results that should be interpreted along with the limitations of the study (sample size, limited time period, challenges of the sentiment analysis following the NLP paradigm). In the following chapters, we juxtapose all the results that were described in the methodology. At the beginning of each country chapter we provide fundamental **contextual and background information such as the social media landscape and the demographics when it comes to the use of different social media platforms, namely Facebook and X in the respective countries. However, the impact of disinformation phenomena are not part of this report.** Following the presentation of the findings corresponding to the different countries, this report proposes a chapter that formulates a synthesis of the results from a comparative perspective.

The methodological instrument designed and implemented for the purposes of the GEO- POWER-EU project aimed at combining the human/ manual as well as the computational evaluation and assessment of sentimental dispositions. The existing literature and recent studies acknowledge that sentiment analysis via NLP presents several limitations as regards its accuracy. However, depending on the datasets that can be scored, there have been very encouraging signs. In our case, the major difficulty was the objective to extract sentiment towards 5 different actors and in 6 different countries and thus languages. From this standpoint, our choice to use computation with a certain precaution was very probably a rather appropriate decision. As it was mentioned, NLP was used both for cross-validation as well as first-level scoring. In the end, nonetheless, it was the human evaluator that had the final say on disagreements. The outcome of this study regards the establishment of procedures and shortcuts that will facilitate the passage to a more developed analytical scheme which should consist in machine learning. The almost 37.000 scored tweets and posts are a valuable database, which will serve to train the fitting software to analyze an even bigger dataset.

Data access and availability

As it was already mentioned, the data collected (Facebook posts and X tweets) were translated from the original language to English and also anonymized prior to being analyzed. As such, they will be available either in the project website or an appropriate institutional depository; they will also be available upon request. Due to ethical and eventual legal constraints, full raw data will not be available. Given that warranted platforms based on automated procedures were used for the translation, it will also be possible to grant access to the social media content in the original language. New insights may appear if the content is studied or analyzed in the language that it was originally written.

Findings: Country Case Studies

Serbia

In Serbia, which currently has a population of approximately 6.7 M (2025), Facebook users account for about 71% of the population (4.8 M) and X users for about 10% of the population (677.8 K) (World Population Review 2025). Furthermore, it is noteworthy that there is a slight majority of female users in Facebook (50.4%), whilst the age groups of 25-34 years and 35-44 years are the most dominant with a cumulative share of 25% for male and 22% for female users (NapoleonCat 2025). As for X, recent data suggest that in Serbia younger adults are also the most dominant age groups, whilst there appears to be an overwhelming majority of male users (approximately 70% male and 30% female regarding X's ad service) (Kemp 2025). The country report on Serbia was concluded in June 2025. The GEO- POWER- EU partners provided a series of keywords in the form of hashtags in an effort to facilitate data collection primarily on X and also Facebook.

Table 4. Key terms and hashtags used for the data collection for Serbia

1. J D. Vance speech	2. Trump - Zelenskyy meeting	3. EU- defence Summit
VensMinhen ВенсМинхен MinhenskaKonferencija МинхенскаКонференција AmerikaMinhenskaKonferencija АмерикаМинхенскаКонференција PotpredsednikMinhentskaKonferencija	ZelenskiTramp ЗеленскиТрамп ZelenskiBelaKuća ЗеленскиБелаКућа ZelenskiTrampVens ЗеленскиТрампВенс ZelenskiSastanakTramp ЗеленскиСастанакТрамп ZelenskiSastanakBelaKuća	EUUkrajinaSamit ЕУУкрајинаСамит EUOdbranaSamit ЕУОдбранаСамит EUUkrajinaOdbrana ЕУУкрајинаОдрбана EvropskaUnijaUkrajinaOdbrana ЕвропскаУнијаУкрајинаОдрбана

1. J D. Vance speech	2. Trump - Zelenskyy meeting	3. EU- defence Summit
ПотпредседникМинхенска Конференција PotpredsednikMinhen ПотпредседникМинхен AmerikaMinhen АмерикаМинхен	ЗеленскиСастанакБелаКућа ZelenskiSastanakVens ЗеленскиСастанакВенс	EvropskaUnijaUkrajinaUjedinjenje ЕвропскаУнијаУкрајинаУједињење EvropskaUnijaUjedinjenje ЕвропскаУнијаУједињење

In Serbia's case, there is the particularity of the use of two alphabets, the Cyrillic and the Latin one. Therefore, we used all the above-mentioned terms in order to collect data (scraping through the platform Apify). Data collection was initiated in early June and it rapidly became clear that by looking for social media content (posts) only through hashtags it would be very difficult to secure a sufficient amount of content. This was a clear confirmation that hashtags are becoming less relevant as facilitators and thematically coherent frameworks that delimitate the circulation of the corresponding X and Facebook posts. However, the limited results as well as the objective to follow a rigorous analytical approach, led us to use the key terms as search terms rather than hashtags.

The data collection for the two platforms differed only about the following aspect. In the case of X tweets, the search terms and geolocation specifications enabled the collection of an ample number of posts. In the case of Facebook, it was necessary to detect specific posts originating with media outlets that are active on Facebook and publish posts that draw the public's attention and generate discussions. In the case of Serbia, we identified such posts from the following outlets (*Večernje Novosti*, *Blic*, *Kurir* and *B92*). It is also important to clarify that as regards Facebook we focused on only one of the three events for the period of study, in particular the meeting between Trump and Zelenskyy at the White House. Thus, the results pertaining to Facebook will merely provide a limited indication regarding the similarities and differences between the two platforms. The following table provides the general results when it comes to the amount of X tweets and Facebook posts collected.

Table 5. The volume of social media content collected for Serbia

	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3
x	1.800	1.700	1.100
Facebook	-	1.200	-

	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)
Total amount of tweets and posts collected: **5.800**			

The data suggest that the most commented and discussed event, on the basis of the duration of the collection period, was the meeting between Trump and Zelenskyy. To a certain extent, this also applies to the first event, the JD Vance speech. On the contrary, the least discussed event seems to be the EU- Defence Summit in early March. Despite the fact that the collection period was long enough, the number of tweets was significantly weaker.

Actor Reference Distribution in the Serbian Sample

The first set of findings regards **the number of references coded per actor and per event.** This is a very important result because it provides a clear indication when it comes to the frequency and the intensity of the discussion regarding the actors. These results are the outcome of the coding performed in order to safeguard that the sentiment analysis will be applied in a systematic and coherent pattern. The following table contains the relevant results.

Table 6. Total amount of references to the actors and per event in the Serbian dataset

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3	
Russia	**1074**	**787**	**430**	***46%***
US	**480**	**563**	**161**	***25%***
EU	**332**	**306**	**324**	***20%***
China	**146**	**120**	**61**	***7%***
Turkey	**52**	**27**	**49**	***2%***
Total amount of references analyzed for X: **4.912** Total amount of tweets and posts collected: **5.800**				
Facebook				
Russia	**-**	**136**	**-**	***32%***

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
US	**-**	**205**	**-**	***49%***
EU	**-**	**60**	**-**	***14%***
China	**-**	**9**	**-**	***3%***
Turkey	**-**	**6**	**-**	***2%***
Total amount of references analyzed for Facebook: **416** Total amount of tweets and posts collected: **5.800**				

The data pertaining to X suggest that almost half of the references coded and analyzed (46%) contained references to Russia. In effect, this trend regarded all three events. In specific terms, this finding suggests that **even in events that were not directly connected with Russia in a strict sense, Russia was the actor with the most frequent connections in the public discussion that took place in X**, as captured by our data. The US and the EU hold a rather comparable share of the references (25% for the US, 20% for the EU), with the EU surpassing the US only in the context of the period regarding the EU defence summit in early March 2025, Certainly,the same parameter could be evoked in the case of the US, since both the J.D. Vance's speech and the Trump- Zelenskyy meeting directly regarded US political figures. China and Turkey are consistently in the fourth and fifth place respectively, with China's references being more frequent than Turkey.

In the case of the data coming from Facebook, the significant differentiation is the domination of references to the US (49%) with Russia holding the second place (32%). With regard to the other actors, one notes important similarities. The EU comes third, China fourth and Turkey fifth. In summing up the presentation of the statistical data on the references coded, it is important to stress that we do not imply that there is a direct and potential connection between the amount and the frequency of the references to the actors and the sentimental dispositions. However, we obtain clear indications of the frequency with which the actors were discussed always in this specific context and succession of events. If we exclude the US which is directly connected with two events, the most remarkable finding is the domination of references to Russia and inversely the very limited amount of references to the EU. This can be an indication of the correlation between the actors, with the US and Russia being the two that may be rather commonly paired in the social media posts. China and Turkey clearly obtained the fewest references, with China clearly being much more frequently evoked in these discussions than Turkey.

Sentiment Results from the Sample of Serbia

The following set of findings regards **the general sentiment scores per actor and per studied events**. This serves the purpose of identifying continuities and discontinuities. However, such patterns have an exploratory character that is primarily connected to the specific period and events and not with more general or macroscopic trends in the sentimental disposition towards the actors.

Table 7. General sentiment score per actor in the Serbian dataset

x	Positive	Negative	Neutral
Collection period	14/2- 14/3		
Russia	**33%**	**39%**	**28%**
US	**36%**	**34%**	**30%**
EU	**25%**	**46%**	**29%**
China	**51%**	**38%**	**10%**
Turkey	**50%**	**32%**	**18%**
Facebook			
Collection period	28/2- 6/3		
Russia	**48%**	**38%**	**14%**
US	**33%**	**45%**	**22%**
EU	**33%**	**50%**	**17%**
China	**45%**	**35%**	**20%**
Turkey	**60%**	**20%**	**20%**

If one takes the three sentiment categories distinctively on X, it is observable that the most positive dispositions are found in the cases of **China and Turkey.** Certainly, they are the actors with the smallest number of tweets, posts and references- in the context of our analysis-, but still the pattern of sentiment distribution in their case is predominantly positive (half of the content relates to positive sentiments with weak neutral scores). The negative disposition is not absent but one cannot evoke a balanced distribution. As regards the three other actors, the **US** is the one with the most significant positive score (36%) on X and the only one- compared to Russia and the EU- whose positive score is higher than the negative and the neutral one. Nonetheless, in the case of the US one cannot really refer to a dominant pattern on X since the distribution of sentiment scores is rather balanced between all three dispositions.

The **EU** is the actor with the weakest overall positive score (25%, compared to Russia's 33%). The negative sentiment is very high (46%), and much higher than the neutral one (29%). **Russia** received a positive score of 33% and in its case one could also evoke a balanced distribution (39% negative and 28% neutral). If we focus on the negative disposition, the EU's highest score (46%) is followed by those of Russia (39%) and China (38%). As regards the neutral disposition, the highest score belongs to the US (30%) with Russia and the EU also receiving comparable scores (28% and 29% respectively).

The sentiment analysis findings from Facebook- which is a far more popular platform in Serbia than X with a 71% share of the population compared to 10% for X- do seem to confirm basic findings from X. For instance China and Turkey received significantly positive scores. Moreover the EU received a highly negative score (50%) which is very close to the one it received on X (46%). On the other hand, one notes two significant differences between X and Facebook regarding the sentimental dispositions towards the US and Russia. Contrary to X, Russia received a very positive score on Facebook and, inversely, the US received a clearly negative score. At a more general level, it is noteworthy that on Facebook we have a significantly smaller amount of neutral scoring, which could be attributed to the bigger length of the posts and subsequently the lengthier references to the actors. On X, on the other hand, the overwhelming majority of the references were shorter, something which may be linked with an important frequency of neutral disposition.

In the following table we present the findings of the sentimental scores per actor and per event. They can help us understand in a more thorough manner the general sentiment score and their fluctuation depending on the event. Nonetheless, it is important to clarify the following element. Given that the period of study was limited (one month) and that the events were close the one to the other, any differentiations should be interpreted as potential indicators and manifestations of shifts caused by the events rather than more general trends in sentimental dispositions. These results will be further connected with the sentiment families constituted for each actor. They will also be correlated with the corresponding results from the other countries.

Event specific shifts in Serbian dataset

Table 8. Sentiment scores per actor and per event in the Serbian dataset.

x	**J.D. Vance speech (14 February)**	**Trump-Zelenskyy meeting (28 February)**	**EU-Defence Summit (6 March)**	**Fluctuation from first to last event**
Collection period	14/2- 14/3			
Russia	**Neg.: 41%**	**37%**	**40%**	**(-1)**
	Pos.: 36%	**33%**	**31%**	**(-5)**

x		J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
	Neut.:	23%	27%	29%	(+6)
US	Neg.:	40%	30%	32%	(-8)
	Pos.:	39%	37%	31%	(-8)
	Neut.:	21%	33%	37%	(+16)
EU	Neg.:	42%	44%	54%	(+12)
	Pos.:	38%	23%	10%	(-28)
	Neut.:	20%	33%	36%	(+16)
China	Neg.:	39%	35%	41%	(+2)
	Pos.:	51%	49%	53%	(+2)
	Neut.:	10%	16%	6%	(+6)
Turkey	Neg.:	35%	23%	38%	(+3)
	Pos.:	49%	50%	52%	(+3)
	Neut.:	16%	27%	10%	(-6)

This table contains multiple data. It is therefore important to break it down in a systematic manner. If we take **Russia** as a first case, it is observable that we don't have a change in sentiment pattern. In all three events, the negative disposition is the one that prevails (at the level of 39%), with the positive coming next and the neutral coming last. However, it is noteworthy that there is a constant decrease in the positive sentiments (from 36% to 31%) and inversely a constant increase in neutral dispositions (from 23% to 29%). Furthermore, the biggest margin between positive and negative dispositions (-9%), occurred in the period of the EU summit (from early to mid-March 2025). Thus, if we had to detect a pattern in Russia's case, this would be the relative domination of negative view, the relative decrease of positive and the relative increase of neutral dispositions.

In the case of the **U.S**, there are clearly more visible shifts in the dynamics. The most negative dispositions are found in the period following the JD Vance speech, the most positive are also found in the same period and the most neutral in the period of the EU Council on Defence. However, in terms of fluctuation, the most important parameter, in quantitative terms, regards the important increase in neutral dispositions. Thus, if we take the JD Vance as the initial point of observation and the EU summit as the final point of observation, the dispositions towards the US became **predominantly more neutral,** but at the same time less negative and also less positive.

In the case of the **EU**, we observe bigger fluctuations. The most negative dispositions are found during the period of the EU summit (54%) and the most positive (38%) in the period of the JD Vance speech. However, there is a clear and consistent pattern of evolution of the sentimental dispositions. There is an important increase in negative dispositions (+12), and neutral dispositions (+16), and a drastic decrease in positive views (-28). This is the single most important fluctuation regarding all actors. It took place progressively but steadily. Beginning with the JD Vance speech, the pattern continued during the period relating to the meeting between Trump and Zelenskyy in the White House and it became even more intense during the period of the EU summit.

In the cases of **China and Turkey**, we note the most stable outlook when it comes to the progression of the disposition patterns throughout the period of study. The positive sentiment is always dominant and even with a slight increase (+2 for China and +3 for Turkey), followed by the negative which is also slightly increased and lastly by the neutral which is the weakest in terms of intensity. Thus, the data indicates that although the references regarding the two countries were fewer than those regarding the other actors, the dispositions seemed to be less dependent or affected by the period and in specific the three events that we chose to study as a group of interrelated developments.

Sentiment families in the Serbian dataset

The final table in this study regards a mapping of several sentiments that fall into the basic categories, namely the positive, the negative and the neutral. The data represent an attempt at exploring the different possibilities to detect such emotional variations and also measure them. It is also founded upon the premise of content analysis and lexicometry. We used the social media content (posts and tweets) that were already scored according to the three categories (positive, neutral and negative) and created a coding scheme on the basis of lexicometry. In essence, for each of the sentiments that we distinguish, we formed a corresponding lexicon of terms that can be associated with them. We thereby implemented a search of the terms per country. In this case, the search was applied to all the content.

The results we obtained are quantitative in nature. In essence, they represent the frequency of the terms that we searched for in the social media content. Instead of presenting this data in a statistical form, we opt to a more general and less definite presentation, in an effort to capture the tendencies and the significant differentiations rather than present them as categorical differences. It is important to note that the labels strong/medium and weak stand for the frequency or the amount of the occurrences of the terms that fall into different categories of emotions.

Table 9. The families of sentiments per actor in the Serbian dataset

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Positive	Status Recognition/ admiration	medium	medium	weak	weak	weak
Positive	Expectations	strong	strong	medium	medium	weak
Positive	Hope/Optimism	strong	medium	medium	weak	weak
Positive	Security	medium	weak	weak	weak	weak
Positive	Similarity	weak	weak	weak	weak	weak
Positive	Trust	weak	weak	weak	weak	weak
Neutral	Confusion/ uncertainty	medium	medium	medium	weak	weak
Neutral	Dissociation	weak	weak	weak	weak	weak
Neutral	Indifference	weak	weak	weak	weak	weak
Neutral	Observation/ absence of emotions	strong	strong	strong	strong	strong
Negative	Betrayal	weak	weak	weak	weak	-
Negative	Frustration	medium	medium	medium	weak	weak
Negative	Distrust	medium	weak	medium	weak	weak
Negative	Insecurity	weak	weak	weak	weak	weak
Negative	Fear	strong	medium	medium	weak	weak
Negative	Manipulation	weak	weak	weak	weak	-

The table provides the opportunity to formulate several interesting remarks per sentiment category. Overall, if one takes into consideration all categories and the results, it is noteworthy that the most comparable actors are Russia, the US and the EU. This is mainly due to the amount of the references analyzed. In the case of China and Turkey, the smaller amount made it more difficult to detect the same variety of emotions as well as the frequency in a more meaningful way. Particularly for the three actors, the EU, the US and Russia, we propose a series of interpretative remarks that present the positive and negative sentiments in a more meaningful way. They are founded on a qualitative synthesis of recurring arguments put forth by the social media users. This is a rudimentary analysis that was enabled by the fact that we opted to group the scored tweets and posts per country according to the three labels (negative, neutral and positive). This allowed us to grasp more easily frequently evoked themes.

Beginning with the positive group, the most important finding is that Russia seems to be the actor that is more frequently and more explicitly connected with the variations of the positive sentiments of expectations, admiration, hope and security. These could be partially attributed to a sense of proximity and affinity expressed by social media users as well as the acknowledgement of Russia's impactful position in international affairs. The US comes next and, arguably, this can be attributed to the effect of President Donald Trump whose actions are frequently presented in a very positive manner. In effect, recent studies suggest that since the election of Donald Trump the government narratives- as well as the narrative of the mainstream media close to government positions- present the US in a much more positive pattern (CRTA, 2025). In effect, we encountered quite often the depiction of the US as a decisive and powerful actor without ideological associations. The EU follows with somewhat less associations with positive emotions and especially the dispositions of admiration or acknowledgement of its status as an impactful actor.

China is also an actor commonly associated with high expectations, something which certainly corresponds to the global impact of its policies. The neutral disposition seems to be mainly associated with an important number of tweets and posts that contain very short and elliptical references to the actors without the use of elements of interpretation or evaluation. A second category, mainly associated with actors such as Russia, the US and the EU is uncertainty, particularly in cases where there is not necessarily a negative tone but the acknowledgement of the difficulty to predict or evaluate the actions of the actor.

In the category of negative dispositions, it is once more Russia, US and EU that are mostly present in several sub-categories. This is particularly the case for Russia and the EU (frustration, distrust and fear), with Russia being very frequently associated with the sentiment of fear and distrust). Evidently, Russia, who was the most discussed actor, seems to be approached in a rather polarized configuration (positive and negative). The aggressive character of its war against Ukraine and its authoritarianism were elements that were present in many tweets and posts. In the case of the US, one notes recurring arguments about the absence of morality, with the exploitation of Ukraine's mineral resources as well as the war against Yugoslavia in 1999 being frequently evoked.

In effect, it is rather the EU that tends to concentrate negative emotional reactions. In its case, a very indicative element is the weaker level of recognition or acknowledgement of its status as an impactful international actor. If one combines it with the high level of distrust and fear, then a rather alarming assessment is at hand. In effect, the negative sentiment towards the EU is frequently manifested through patterns of disappointment and disengagement fueled by the stagnation of the process of Serbia's EU accession, with hypocrisy being a common theme. China's and Turkey's scores were constantly positive; however,due to the smaller amount of data, our instrument was not able to detect more palpable and subtle manifestations of emotional reactions. Nonetheless, it is noteworthy that the positive sentiment for China includes the perception of the economic advantages for Serbia if it strengthens its cooperation with China. The negative, on the other hand, relates in some cases to a criticism of its authoritarianism as a political system. For Turkey, the arguments within the positive and the negative sentiment appear to be somewhat contradictory, since in the positive there is a perception of Turkey as a regional partner but in the negative there is the idea that Serbia needs to be overcareful and suspicious towards Turkey.

Key takeaways from the Serbian case study

Our study as regards the Serbian context gives us the opportunity to formulate the following general remarks. Russia was certainly the most discussed actor on X and the second most discussed actor on Facebook. It was also the actor with the most polarized emotional profile (slightly negative on X but clearly positive on Facebook). The same pattern was also discernable in its association with the different categories of emotions: it was most associated with positive emotions (i.e. expectation, admiration, hope) but also the most frequently linked with fear. As regards the US, which was along with Russia the most discussed actor (first on Facebook, second on X), one notes a rather indecisive and polarized sentimental profile on X but a more clearly negative profile on Facebook. Nonetheless, it is important to take notice of the significant share of positive reactions that it received on X and which arguably could be linked with the discussion and the anticipation surrounding President Trump's policies on global affairs. In the case of the EU, which holds an intermediary position when it comes to the number of references in which it was present (significantly less than the US and Russia but also significantly more than China and Turkey), we note the strongest association with negative emotions (in both platforms). In effect, it is the actor with the biggest margins between negative and positive sentiments. It is also the actor with the weaker connections to positive emotions (i.e. admiration, hope or expectations). Lastly, in the case of China and Turkey, the two least discussed actors, one notes predominantly positive scores (on both platforms).

North Macedonia

In North Macedonia, which currently has a population of approximately 1.8 M, Facebook users account for 71% of the total population (1.4 M) and X users account for 7% (125 K) (World Population Review 2025). Male Facebook users appear to be more numerous (52.1%). Moreover, the age groups of 25 to 34 years and 35 to 44 years are the two most dominant (cumulative share of 27% for male and 23% for female users), followed by the group of 45 to 54 years (NapoleonCat 2025). In the case of X, there appears to exist an overwhelming majority of male users, if one takes into account the platform's ad audience (Kemp 2025). The country report on North Macedonia was concluded in early July 2025. The GEO- POWER- EU partners provided the following series of keywords in the form of hashtags in an effort to facilitate data collection primarily on X and also Facebook

Table 10. Key terms and hashtags used for the data collection for North Macedonia

1. J D. Vance speech	2. Trump - Zelenskyy meeting	3. EU- defence Summit
#MSC2025 #Минхен #конференција #Минхен #конференција #Украина #Зеленски #Венс	#трамп #зеленски #средба #кавга	#еусамит #одбрана #ЕУ #самит
In an effort to maximize data collection, we added the following search terms for all cases: “Европската Унија”, “Европа”, “Соединетите Американски Држави”, “Америка”, “САД”, “Русија”, “Кина” and “Турција”.		

In the case of North Macedonia, most of the posts on the two social media platforms were written in the Cyrillic alphabet, used predominantly for all purposes and contexts, formal and informal. However, we did detect a very small number of posts that were written in the Latin alphabet. All methodological specifications (data collection, scraping) were applied without any differentiation when compared to the other countries. As with the other case studies, we established a pool of several news media, blogs and sites- of various political orientations and with an active presence on the platform- with a view to obtain a content as representative as possible. In the case of Facebook our sample included the following sites: *24info.mk, A1.mk, Sitel.mk, 24.mk, infomax.mk, kanal5.mk, makfax.mk, plusinfo.mk, telma.mk, skopje1.mk*. Similarly to all other case studies, in the case of Facebook we focused on the second event studied, namely the visit of Ukrainian president Zelenskyy in the White House in late February. The following table informs on the total number of tweets and posts collected and analyzed for North Macedonia.

Table 11. The volume of social media content collected for North Macedonia

	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3
x	1100	1000	500
Facebook	-	1200	-
Total amount of tweets and posts collected: **3800**			

The data indicate that the two first events, in a chronological order, namely the speech by the vice president of the US, JD Vance, as well as the meeting between presidents Trump and Zelenskyy at the White House, drew more attention and provoked more reactions and comments by the social media users in North Macedonia. On the contrary, the EU Council on Defence was much less discussed, always according to our sample.

Actor Reference Distribution in the Sample of North Macedonia

The next set of findings provides a clear view on the quantity of references detected and analyzed per actor and per event. This is a very substantial indication of the frequency and the intensity with which the international actors were discussed by the social media users in North Macedonia. As in all case studies, the coding that we applied safeguards that the analysis of the sentiment regarding the actors is performed on the specific part of the content that concerns them.

Table 12. Total amount of references to the actors and per event in the North Macedonian dataset

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3	
Russia	**248**	**202**	**149**	***24%***
US	**453**	**348**	**101**	***36%***
EU	**346**	**252**	**153**	***30%***
China	**51**	**59**	**30**	***6%***
Turkey	**14**	**22**	**18**	***4%***
Total amount of references analyzed for X: **2446** Total amount of tweets and posts collected: **3800**				
Facebook				
Russia	**-**	**149**	**-**	***32%***
US	**-**	**201**	**-**	***43%***
EU	**-**	**98**	**-**	***20%***
China	**-**	**11**	**-**	***3%***

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Turkey	**-**	**8**	**-**	***2%***
Total amount of references analyzed for Facebook: **467** Total amount of tweets and posts collected: **3800**				

In the case of X, the data confirm that for all actors there seems to be a progressive decrease in the numbers of references analyzed, which in effect mirrors the decrease of tweets published towards the end of the period. Therefore, it is likely that the peak for the discussions, in terms of intensity, was centered mostly around the reverberations of the speech by JD Vance and the meeting between presidents Trump and Zelenskyy. By the time that the EU defence summit took place, the discussion- as we captured it with our data- was losing its momentum and was becoming less active. The group of the three actors with the most references included the EU, Russia and the US. Between them they shared almost 90% of the references. This also applies in the case of Facebook. Inversely, China and Turkey have a combined share of 10%.

When it comes to actors, the references to the US in X were present in more than one third of the total number of tweets (36%). The EU came second with an important portion of the tweets (30%) followed by Russia (24%). The important number of references to the US is rather expectable, given that two out of the three events relate directly to the country and its highest-ranking officials. In effect, the differences among the three actors (Russia, US and EU) are not such that one could evoke an occurrence difficult to interpret. Commonly all three of them are present in the same post. In the case of North Macedonia, nonetheless, it is noteworthy that the references to the EU are more significant than those to Russia. On the other hand, China and Turkey are present in a very small number of tweets, particularly Turkey. In the case of China, one can observe the same decrease in the number of tweets towards the end of the period. It is another confirmation that by the time of the EU defence summit in early March the debates and the discussions spawned by JD Vance's speech and the meeting in the White House were calming down.

On the other hand, the data regarding Facebook tell a somewhat different story. The US is still the actor with the highest number of references (43%) -Russia comes second (32%) and the EU third (20%). China and Turkey are present in a very small number of posts.

Sentiment Results from the sample of North Macedonia

Table 13. General sentiment score per actor in the North Macedonian dataset

x	Positive	Negative	Neutral
Collection period	14/2- 14/3		
Russia	**25%**	**35%**	**40%**
US	**20%**	**34%**	**46%**
EU	**22%**	**38%**	**40%**
China	**40%**	**20%**	**40%**
Turkey	**33%**	**25%**	**42%**
Facebook			
Collection period	28/2- 6/3		
Russia	**40%**	**24%**	**36%**
US	**23%**	**30%**	**47%**
EU	**21%**	**52%**	**27%**
China	**57%**	**15%**	**28%**
Turkey	**39%**	**41%**	**20%**

The EU has the most negative score. Furthermore, the EU presents the most important margin between positive and negative dispositions (38% negative and 22% positive), compared to Russia (35% negative and 25% positive) and the US (34% negative and 20% positive). In terms of positive dispositions, Russia received the most positive score (25%), followed by the EU (22%) and the US (20%).On the basis of this data we can formulate the following two remarks: i) in general terms, if we set aside the neutral disposition, the negative tone is clearly more dominant than the positive across all cases, ii) **in terms of outlook or general profile, the most definite patterns seem to regard the negative disposition towards the EU and the US**.

In the case of China and Turkey, there is a positive outlook, although the neutral dispositions are very comparable to the ones pertaining to the other actors. China presents the highest score in positive dispositions as well as the most important margin (40% positive and 20% negative, margin of 20). Turkey also received a significant positive score (33%) but with a smaller margin (25% negative, margin of 8). Therefore, the **third remark that can be formulated more safely regards the positive outlook regarding China**.

Regarding the sentiment analysis of Facebook posts, one notes several similarities, and one major discrepancy. For the US and the EU, the negative disposition is once more the most dominant.

However, in the case of the US the results are very comparable to the ones in X, whilst in the case of the EU, the outlook is much more definite. In effect, the negative dispositions regarding the EU on Facebook reached 52% (38% on X) whilst the margin between negative and positive was 29 for Facebook. Contrary to X, Russia received a positive score of 40% on Facebook and with a very important margin (24% negative). In the case of China and Turkey, one notes the impressive positive score for China (57%) and also the negative score for Turkey (41%). However, the collected posts for both actors were very few and it is difficult to claim that these results validate the identification of a clear pattern. From this standpoint, the **most clearly and substantially identified patterns on Facebook, regard the positive score of Russia, the negative score of the EU and also of the US**. The following table provides the results regarding the sentiment score per actor and per event on X.

Event specific shifts in the North Macedonia dataset

Table 14. Sentiment scores per actor and per event in the North Macedonian dataset

x	**J.D. Vance speech (14 February)**	**Trump-Zelenskyy meeting (28 February)**	**EU-Defence Summit (6 March)**	**Fluctuation from first to last event**
Collection period	14/2- 14/3			
Russia	**Neg.: 36%**	**36%**	**34%**	**(-2)**
	Pos.: 26%	**24%**	**25%**	**(-1)**
	Neut.: 38%	**40%**	**41%**	**(+3)**
US	**Neg.: 35%**	**35%**	**33%**	**(-2)**
	Pos.: 25%	**18%**	**19%**	**(-6)**
	Neut.: 40%	**47%**	**48%**	**(+8)**
EU	**Neg.: 45%**	**33%**	**38%**	**(-7)**
	Pos.: 18%	**23%**	**26%**	**(+8)**
	Neut.: 37%	**44%**	**36%**	**(-1)**
	Neg.: 20%	**17%**	**23%**	**(+3)**

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
China	Pos.: 38%	39%	44%	(+6)
	Neut.: 42%	44%	33%	(-11)
Turkey	Neg.: 20%	32%	23%	(+3)
	Pos.: 33%	31%	36%	(+3)
	Neut.: 47%	37%	41%	(-6)

As with all case studies, this table helps to explore the fluctuations in the sentiment dispositions towards the actors, based on the succession of the events used as frames of reference. Beginning with the group of the three actors, Russia, US and EU, it is clearly **Russia** the one with the weakest signs of fluctuation and variations in the three sentiment categories. The neutral is steadily the most important category, followed by the negative and lastly the positive. However, the margins are stable and there is no fluctuation that implies a change that could be correlated with the three events. In the case of the US and EU, one notes notable differences. When it comes to **the US**, there are important fluctuations that regard mainly the neutral and the positive dispositions. Whilst the negative remained stable, there was an important increase in the neutral dispositions as well as an important decrease in the positive dispositions. Thus, there appears to be a shift that is substantial enough and that could be potentially linked with the successive events. Also, in the case of the **EU,** one notes important fluctuations, particularly when it comes to the negative and the positive dispositions. In both cases, there seems to be a progressive transformation.

As regards the negative dispositions towards the EU, there is a decrease from 45% (beginning of the period) to 38% (end of the period), whereas in the case of the positive dispositions there is an increase of 8% (18% in the beginning, 26% in the end). In the case of China and Turkey, there were also noticeable fluctuations. For China, such changes regarded the important increase in positive dispositions and the decrease in neutral ones. In the case of Turkey, there was also a decrease in neutral dispositions and a relative increase in both negative and positive ones. Nonetheless, as it was noted earlier, the limited quantity of tweets in both cases, particularly for Turkey, leads us to a more measured acknowledgement of these findings.

In summing up the key findings from this set of results, Russia presented the most stable configuration in terms of sentimental dispositions during the period of interest. All parameters, neutral, negative and positive, showed very little signs of variation. It was, in effect, the sentimental dispositions towards the EU and the US that presented significant fluctuations. **The EU's outlook**

became more positive and less negative and the US's outlook became less positive and more neutral in the course of this historic month.

Sentiment Families in the North Macedonia dataset

With our next set of results and findings, the mapping of the sentiment families associated with the actors, we made the effort to provide another layer of data with a view to rendering the sentimental dispositions more visible and accessible. Similarly to all other cases, the following results are based on the application of a coding lexicon that seeks to identify a series of sentiments within the larger families of neutral, positive and negative dispositions. In this case, the lexicon was applied to all data (X and Facebook). Furthermore, it is important to stress that this mapping of sentiments holds an exploratory character. In other words, the results aim at providing helpful insights rather than categorical outcomes based on statistics. The following table presents the corresponding findings.

Table 15. The families of sentiment per actor in the North Macedonian dataset

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Positive	Status Recogn/ admiration	Strong	Strong	Medium	Medium	Weak
Positive	Expectations	Strong	Strong	Strong	Medium	Weak
Positive	Hope/Optimism	Strong	Strong	Strong	Weak	Weak
Positive	Security	Strong	Strong	Strong	Weak	Weak
Positive	Similarity/Affinity	Strong	Strong	Weak	Medium	-
Positive	Trust	Weak	Strong	Weak	Weak	-
Neutral	Confusion/ uncertainty	Medium	Medium	Strong	Weak	Weak
Neutral	Dissociation	-	-	-	-	-
Neutral	Indifference	-	Weak	Weak	Weak	-
Neutral	Observation/ absence of emotions	Strong	Strong	Strong	Medium	Weak
Negative	Betrayal	Weak	Weak	Weak	-	-
Negative	Frustration	Strong	Strong	Strong	Weak	Weak
Negative	Distrust	Medium	Medium	Strong	Weak	Weak
Negative	Insecurity	Medium	Medium	Medium	-	-
Negative	Fear	Medium	Medium	Medium	Weak	Weak
Negative	Manipulation	Medium	Weak	Weak	-	-

In broad terms, the results confirm once more that most commonly, the expression of various emotions towards the three actors (Russia, US and EU) is much more nuanced and intense. It is quite the opposite in the case of China and Turkey, something which is certainly linked with the smaller number of posts referring to the two actors. Also, it is observable that among the three actors (Russia, US and EU) Russia and the US present more similarities than differences. In almost all cases they obtain comparable results. **Therefore, it seems that it is the EU which, in terms of emotional pattern, seems to stand alone**. China received much more emotional reactions than Turkey.

If we focus on the positive pole, it is remarkable that both Russia and the US received similarly high frequencies of the various emotions (status recognition/ admiration, expectations, hope, security, affinity) with the exception of trust (more for the US). The positive sentiment towards the US appears to evolve around elements of pragmatism and realism (the US as a powerful actor that can impose solutions and that is also linked with security guarantees). The positive for Russia relates to themes of affinity (weaker than Serbia) or of its role as a counterweight to the Western hegemony. On the contrary, the EU pattern differs in three aspects: firstly, the status recognition/ admiration which refers to the lower frequency of references to the EU as a "global power/ superpower", the affinity and lastly trust. In effect, the EU was the actor which received the most negative score. In simple terms, it seems that the positive sentiment for the EU has been expressed in a more indirect and less engaged manner and without the use of strong terminology. It could be argued that the positive sentiment for the EU was expressed less enthusiastically than in the case of Russia and the US. Commonly, the positive themes included the economic advantages of stronger ties to the EU. Lastly, it is also obvious that China received a substantial number of posts with terminology relating to positive emotions. However, it stands in an intermediary position, less than the three actors and more than Turkey. In the neutral category, there are similarities between the actors. This category, classified as neutral, entails the absence or the weak presence of emotionally charged terminology. This is validated by the fact that most actors received high scores in the category "observation/ absence of emotions". Nevertheless, there is at least one element of differentiation which regards the EU and the high score that it obtained in the "confusion and uncertainty" category.

In the negative pole, the higher score that Russia received is found in the category "manipulation" and the higher score that the EU received in the category "distrust". The difference in the symbolic expression of the emotional response to the actors is once more palpable by the following trait: In the case of Turkey and China, we were not able to detect any expression or use of terminology that refers to "manipulation", "insecurity" and "betrayal". This is not only related to the smaller number of tweets and posts. It is also the confirmation of the difference in the perception of the emotional connection to the actor. In the case of North Macedonia, as in other cases, the emotional reactions of social media users towards Russia, EU and the US reveal an important degree of tension, which if we judge by the quantitative dimensions is commonly negative. The negative sentiment towards the EU, particularly ''distrust'', seems to be motivated frequently by its failure to acknowledge the sacrifices that North Macedonia made (disputes with neighboring countries such as Greece and Bulgaria) resulting in a stagnation of its accession process. The negative dispositions towards the US appear to be linked with perceptions of its acute cynicism and absence of moral standards in its international policies. As regards Russia, we often detected themes that relate to its expansionist and repressive policies and more generally the destabilizing effects of its role in the region of South-East Europe and beyond. Lastly in the case of China and Turkey we can formulate the following remarks, despite the much smaller sample. The positive for China relates once more to perceptions of its economic power and the negative to the opaque nature of its political objectives and influence. For Turkey, the positive includes the theme of important partnership (bilateral and regional) and the negative the idea of its opportunistic strategy.

Key takeaways from the North Macedonian case study

The country report on North Macedonia shows, **firstly**, that the actor that was more present in the posts was the US (36%), followed by the EU (30%) and Russia (24%). **Secondly**, in terms of the overall sentiment score, the EU received the most negative score (38%) compared to Russia (35%) and the US (34%). Russia received the most positive score (25%), compared to the EU (22%) and the US (20%), while the US received the most neutral score (46%). Given the margin between negative and positive score, in the case of the EU we could certainly evoke a more definite finding. The overall sentiment score for China and Turkey was much more positive and less negative. The results from Facebook provided a very important differentiation, the very positive score for Russia, contrary to the findings from X. **Thirdly**, when it comes to the fluctuation within the period of study, we note two major findings: i) the steady increase in positive and the decrease in negative views for the EU, and the decrease in positive and the increase in neutral for the US.

Lastly, the mapping of the sentiment families confirms that it was mainly the profile of the EU which presented notable differentiations among the three actors, something which could be associated with the overall sentiment score for the actor. In general terms, and with the exception of China and Turkey (and also the results from Facebook about Russia), the negative and the neutral sentiments are very dominant.

Bosnia and Herzegovina

In the case of Bosnia and Herzegovina with a population currently standing at approximately 3.1 M, Facebook users account for 64% of the total population (2.0 M) and X users account for 5% (161.2 K) of the population (World Population Review 2025). There appears to exist a strong balance between male and female users for Facebook (50.2% for female and 49.8% for male users), whilst the most dominant age group is that of 25-34 years (27.2%), followed by those of 35-44 years (19.7%) and 18-24 years (18.1%) (NapoleonCat 2025). In the case of X, male users are estimated at the level of 70% and female users at the level of 30% depending on the ad reach of the platform (Kemp 2025). The report on Bosnia and Herzegovina was prepared from mid to late September 2025. A series of pertinent hashtags and keywords were provided by the GEO- POWER- EU partners with a view to facilitating data collection primarily on X and also Facebook.

Table 16. Key terms and hashtags used for the data collection for BiH

1. J D. Vance speech	2. Trump - Zelenskyy meeting	3. EU- defence Summit
• #WesternBalkans • #ZapadniBalkan • #MSC • #MunichSecurityConference • #MinhenskaSigurnosnaKonferencija • #MinhenskaBezbednosnaKonferencija • #JDVance • #JDVens • #Vens	• #TrumpZelenskyy • #TrampZelenski • #Ukrajina • #UkraineWar • #Rusija • #RatuUkrajini	• ##EUOdbrana • #EUDefense • #EUDefence • #Odbrana • #Defense • #Defence • #Ukrajina • #Ukraine • #EnlargementthroughDefense • #EnlargementthroughDefence • #ProsirenjekrozOdbranu • #EUMirovneSnage • #EUPeacekeepers • #Defensiverearmament • #Odbrambenonaoruzavanje • #RearmEurope • #Rearm
In an effort to maximize data collection, we added the following search terms for all cases: "Sjedinjene Američke Države", "SAD" (United States of America, USA), "Rusija" (Russia), "Evropska Unija", "EU" (European Union, EU), "Kina" (China), "Turska" (Turkey).		

Regarding scraping and data collection, our approach was modified to a certain extent. On the basis of the valuable insight provided by the colleagues of the respective team, it was established that the reliance on hashtags for X would be very precarious. Moreover, the very weak use of X in Bosnia and Herzegovina created an additional obstacle when it comes to safeguarding the collection of a sizable data sample for analysis. Therefore, in the case of Bosnia and Herzegovina, our primary analytical focus was Facebook and the secondary was X.

In particular, we collected data, in essence Facebook posts, for all three sub-periods and events: i) the speech by the vice-president of the US, JD Vance (14 mid to late February), ii) the meeting between the presidents of the US, Donald Trump, and Ukraine, Volodymyr Zelenskyy, in the White House (late February- early March) and iii) EU Council regarding matters of security (early to mid-March). In the case of Bosnia and Herzegovina, the data collected from X regarded only the second event and sub-period, the meeting between presidents Trump and Zelenskyy. In both platforms (X and Facebook) the search for tweets and posts yielded rather insufficient results. On the contrary, the use of the hashtags as search terms within the specific timeframes corresponding to each event and sub-period made possible the collection of a significant amount of data. In the vast majority of cases, the text was written in the Latin alphabet pertaining to the language of the country (BHS: Bosnian, Croatian and Serbia). There was also a rather small fraction of texts written in the Cyrillic alphabet.

In the case of Bosnia and Herzegovina, it was imperative to take into account the specificity of similar languages being spoken in neighboring countries like Serbia, Croatia and Montenegro. In this regard, this case presented strong similarities with Moldova. As in all other country studies, we applied very strict specifications for geolocation in order to safeguard that the X tweets and Facebook posts that we will analyze will come, to the greatest degree possible, from locations in Bosnia and Herzegovina. Indeed, the overwhelming majority of tweets and mostly posts came from cities such as Sarajevo, Banja Luka, Mostar, Zenica and Tuzla. As in other cases, there was a minimal amount of texts, mostly tweets, that were written in different languages (i.e. French, German). This meant that they were published by individuals that reside in Bosnia and Herzegovina. In these cases, we simply disregarded such content since commonly it remained untranslated. Another crucial challenge in the case of Bosnia and Herzegovina, regarded the collection of a sufficient amount of Facebook posts for analysis.

Accordingly, we established an extensive list of media that are active on Facebook and (mostly news media and blogs) that cover all three ethnic communities and also the two federal entities, the Federation of Bosnia and Herzegovina and the Republika Srpska. We included the following: *Klix.ba, Dnevni Avaz, Oslobodjenje, Radio Sarajevo, N1 BiH, BHRT-BHT1, Raport.ba, Istraga.ba, Buka, Tacno.net, Vijesti.ba, RTRS, ATV, BN Televizija, Nezavisne novine, Glas Srpske, faktor.ba, TVSA, Hayat TV, RTV HB, Dnevnik, Bljesak, Vecernji List*. For each and every of the above-mentioned outlets, we employed all the hashtags, by using them as search terms, in order to identify posts relevant to the three sub-periods and events with an important number of comments and replies. We managed to collect the corresponding data almost from all sources, even though the proportions were not necessarily even. In the case of X, our task was more simplified, since our focus was only the second sub-period and event, the meeting between presidents Trump and Zelenskyy at the White House in late February. The following table contains the corresponding information:

Table 17. The volume of social media content collected for BiH

	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3
X	-	515	-
Facebook	1840	2750	1230
Total amount of tweets and posts collected: **6335**			

The figures indicate a sharp contrast between the amount of data collected for X and for Facebook. If we focus on the second sub-period and event, the Trump -Zelenskyy meeting, it is evident that our effort yielded a clearly bigger amount for Facebook. On the one hand, this is evidently linked to our enlarged sample of sources for collection. On the other hand, it is a confirmation that Facebook appears to be much more preferred by Bosnian citizens when it comes to discussing and debating topics relating to international affairs. Thus, in this context, the decision to focus primarily on Facebook and use X as a second option to obtain a measure of comparison appears to be clearly justified. Furthermore, it is notable that the figures confirm trends already noted in the other countries. One notes that the second event (the Trump- Zelenskyy meeting) was the most discussed and referred to by the Bosnian public. Another similarity regards the sharp decline of posts from the second to the third period (the EU summit on defense), something which indicates that the event in question was not discussed and debated with the same intensity. As we observed in the previous studies and contrary to X, the amount of Facebook posts do not necessarily translate into an equal number of references to the actors (EU, US, Russia, China and Turkey). The posts containing explicit references to the actors are inferior to the general sum of the posts. Nonetheless, as it will be shown, in the case of Bosnia and Herzegovina the significant number of posts ensured that we obtained an equally substantial number of posts with references to the actors.

Actor Reference Distribution from the Sample of BiH

The results regarding the number of references analyzed per actor and per event on the two platforms provide a useful insight that potentially highlights the interest and the intensity with which a part of the Bosnian public- as it was captured by our collection- discusses in regard to the actors.

Table 18. Total amount of references to the actors and per event in the BiH dataset

x	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3	
Russia	**-**	**289**	**-**	***42%***
US	**-**	**176**	**-**	***26%***
EU	**-**	**126**	**-**	***18%***
China	**-**	**36**	**-**	***5%***
Turkey	**-**	**59**	**-**	***9%***
Total amount of references analyzed for X: **686** Total amount of tweets and posts collected: 6335				
Facebook				
Russia	**322**	**337**	**164**	***36%***

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
US	**305**	**426**	**120**	***37%***
EU	**213**	**195**	**145**	***24%***
China	**16**	**14**	**7**	***2%***
Turkey	**12**	**8**	**5**	***1%***
Total amount of references analyzed for Facebook: **2289** Total amount of tweets and posts collected: 6335				

The data show that the US and Russia are the actors that commonly occupy the first and the second position with a certain margin from the other actors as regards both platforms. Furthermore, it is once more the EU which holds a rather intermediary position, whilst China and Turkey are found in a very limited number of references. Another similarity regards the progressive decline in the quantity of references- in Bosnia and Herzegovina this applies to Facebook- from the second to the third event. On the other hand, there are also some minor divergences. For instance, it is noteworthy that in the case of the second event (the Trump- Zelenskyy meeting) in relation to platform X, the references to Russia are far superior to those to the US. It is a remarkable finding; however, we cannot interpret it in a safer way since we focused only on this sub-period.

Bosnia and Herzegovina is the only country where Turkey (9%) is more referenced than China (5%) in X. However, on Facebook these references are limited and very comparable to the levels noted in the other country studies. The US and Russia are the two actors that provoke the most intensive discussion and debates. For the US, this is certainly linked with the two first events (JD Vance speech and Trump-Zelenskyy meeting) and for Russia it can be attributed to the importance of the question of Ukraine, particularly in the second sub- period and event.

In the case of X, the total amount of tweets collected was 515 but the amount of references analyzed was 686. This is the result of the fact that many tweets contained references to more than one actor, especially the US and Russia, or the EU and Russia. In this regard, it seems that in a very important portion of the tweets there were very frequent references to Russia, something which clearly indicates the multiple connections and the correlations between this actor and the developments in the White House, always according to the specific sample that we collected. On the contrary, in the case of Facebook the figures are very comparable to those of the other country studies. The number of posts collected (5820) is far superior than that of the analyzed references (2289). It is an element already established elsewhere. Taking into consideration that we extracted the totality of posts (comments and replies) that corresponded to a particular discussion initiated by the initial post of a media outlet, we took notice of a very important number of posts with a content that was totally unrelated to the actors or that contained a very minimal textual expression (i.e. few words, direct response to another user or other users in general). Our target in all cases was to focus and analyze the explicit references to the actors. This was a fundamental aspect when it comes to the extraction of the sentiment score. Certainly, this is also a limitation of our study and sentiment analysis. Nonetheless, we have already stressed that our goal is to provide verifiable and consistent results that will not be coated with claims of a wider application or interpretation of the general public's attitudes in the specific country. Our results provide indications within the given limits of the sample collected. The following table provides the general sentiment score per actor on both platforms.

Sentiment results from the sample of BiH

Table 19. General sentiment score per actor in the BiH dataset

x	Positive	Negative	Neutral
Collection period	28/2- 6/3		
Russia	**30%**	**28%**	**42%**
US	**31%**	**22%**	**47%**
EU	**22%**	**36%**	**42%**
China	**33%**	**14%**	**53%**
Turkey	**51%**	**11%**	**38%**
Facebook			
Collection period	14/2- 14/3		
Russia	**28%**	**37%**	**35%**
US	**18%**	**44%**	**38%**
EU	**19%**	**42%**	**39%**
China	**28%**	**16%**	**56%**
Turkey	**24%**	**43%**	**33%**

There is a domination of negative dispositions towards the three actors who were mostly referred to by Facebook users, in particular Russia, the US and the EU. In the case of Facebook, China and Turkey were present in very few posts, therefore it would be very risky to evoke a particular trend or outlook. Towards Russia one notes the smallest margin between negative and positive dispositions (37% negative and 28% positive, margin of 8 points). In the cases of the U.S. and EU, the negative score is more than double of the positive: for the US we note a 44% negative and 18% for positive (margin of 26 points) and for the EU a negative score of 42% compared to a 19% for positive (margin of 22 points). Moreover, in all three cases, the neutral dispositions are inferior to the negative ones, something which is likely an indicator of the intense and somewhat explicit expression of the sentimental dispositions and attitudes. Such figures indicate negativity to the main international actors. The empirical aspect of our analysis mainly guides us to remark that when we compare the dispositions towards the three actors we do not really take notice of major differentiations, with a minor clarification that Russia's outlook is less negative than the one for the EU and the US.

The results from X tell a different story. The positive dispositions, especially towards the US, China and Turkey, are clearly dominant in X, whilst Russia's outlook is more balanced and the one for the EU is the most negative. Considering that we were able to collect more meaningful tweets for China and even more so Turkey, it is necessary to take notice of the overwhelmingly positive score for Turkey (51% positive and 11% negative) and also China (33% positive, 14% negative). In effect, the only result that presents a strong similarity with the one on Facebook is the score for the EU. It is clearly negative in both cases, something which could indicate the negative sentiment towards the EU. The positive outlook for the US and the balanced outlook for Russia is in sharp contrast with the results from Facebook. In all, it is certain that the data from Facebook were significantly more ample and, accordingly, it would be important to take a closer look at the fluctuations of sentimental dispositions as regards this platform during the period of study. The following table provides this exact view.

Event specific shifts in the BiH dataset

Table 20. Sentiment scores per actor and per event in the BiH dataset

Facebook	**J.D. Vance speech (14 February)**	**Trump-Zelenskyy meeting (28 February)**	**EU-Defence Summit (6 March)**	**Fluctuation from first to last event**
Collection period	14/2- 14/3			
Russia	**Neg.: 38%**	**34%**	**38%**	**(0)**
	Pos.: 23%	**35%**	**28%**	**(+5)**
	Neut.: 39%	**31%**	**34%**	**(-5)**
US	**Neg.: 49%**	**39%**	**45%**	**(-4)**
	Pos.: 16%	**22%**	**16%**	**(0)**

Facebook	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
	Neut.: 35%	39%	39%	(+4)
EU	Neg.: 48%	41%	37%	(-11)
	Pos.: 15%	16%	24%	(+9)
	Neut.: 37%	43%	39%	(+2)
China	Neg.: 12%	15%	20%	(+8)
	Pos.: 33%	30%	20%	(-13)
	Neut.: 55%	55%	60%	(+5)
Turkey	Neg.: 40%	40%	50%	(+10)
	Pos.: 30%	20%	20%	(-10)
	Neut.: 30%	40%	30%	(0)

If we focus on the three actors with most references on Facebook, Russia, US and EU, we note several differentiations. In the case of Russia, the outlook remains negative throughout the period with some noticeable variations. Russia presented the highest positive score, compared to the US and the EU. There is fluctuation of the positive dispositions between JD Vance's speech and Trump-Zelenskyy meeting, i (from 23 to 28, +5 points). Still, the negative dispositions remained unchanged and clearly more frequent. Only in the second event, the Trump-Zelenskyy meeting, do we notice an increase of the positive and a decrease of the negative and subsequently equal sizes. In the case of the US, the outlook also remained negative but with a clearer gap between negative and positive (45% negative and 16% positive at the end of the period). There was a slight decrease in the negative dispositions (49% in the beginning and 45% in the end), whilst the positive remained at the level of 16%.

Also, for the EU there was variation in the second sub-period and event (Trump- Zelenskyy meeting), there was an important decrease of negative dispositions (from 49% to 39%) and also an increase in the positive ones (from 16% to 22%). However, as was mentioned, this did not persist towards the end of the period. Lastly, in the case of the EU, one could evoke a pattern of evolution that was consistent throughout the period, even though it did not alter the general outlook, which was negative (37 negative and 24% positive). However, there was a sharp decrease of negative sentiment (from 48% to 41% and finally to 37%) and a more modest increase of positive sentiment (from 15% to 16% and finally to 24%). Still, such a dynamic cannot be overemphasized since it does not alter the general direction. Overall, our analysis established widespread negativity. In other words, we found no evidence or rather indication or element that would potentially suggest a correlation, the hypothesis that the negative dispositions towards one actor could translate into positive dispositions towards the other or others. In most, if not all, cases the negative sentiment prevailed. In the case of China and Turkey, it would be preferable not to risk to evoke any discernable pattern due to the very limited number of Facebook posts collected and analyzed (a few dozens in total for both actors).

Sentiment families in the BiH dataset

We encountered two types of insights regarding the positive or the negative feeling by the Facebook users in Bosnia and Herzegovina towards the actors: firstly, those that relate to the actors' policies vis-a- vis Ukraine and other aspects of international affairs (EU- US relations, EU-Russia relations and US-Russia relations) and second, those that regard Bosnian politics. In the case of Bosnia and Herzegovina, it would be riskier to single out a few arguments for positive or negative sentiment, since it is more complicated to correlate it with a particular part of the population and more importantly with the different communities. Thus, it would be more pertinent to note that, in this case, as in the others, we found similar arguments (i.e. negative views about Russia as a country that initiated an act of unjustified aggression against a neighbor, negative views about the US as an unreliable partner that is interested in securing economic gains at the expense of a country at war and negative views towards the EU for its weaknesses and lack of unity when it comes to foreign policy and security and also for being also more interested in securing economic gains from Ukraine). This listing is merely indicative and serves as a means to connect with the more qualitative aspect of the data and particularly the negative sentiments that were so present. It should also be clarified that for China and Turkey we do not present any result due to the very limited number of tweets and posts that make it difficult to quantify the occurrence of certain terms. Nevertheless, it is observable that China is praised for its pragmatism and decisiveness when it comes to the economy (i..e investments) but also criticized for its lack of transparency. As regards Turkey, some of the positive comments praise the historical ties with Bosnia and Herzegovina and its genuine solidarity and support, whilst some of the negative present it as a paternalistic and self- interested actor.

Table 21. The families of sentiments per actor in the BiH dataset

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Positive	Status Recognition	strong	medium	medium	-	-
Positive	Expectations	strong	medium	medium	-	-
Positive	Hope/Optimism	medium	weak	medium	-	-
Positive	Security	weak	weak	weak	-	-
Positive	Similarity/Affinity	medium	weak	medium	-	-
Positive	Trust	weak	weak	weak	-	-

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Neutral	Confusion/ uncertainty	medium	medium	medium	-	-
Neutral	Dissociation	medium	medium	medium	-	-
Neutral	Indifference	medium	medium	medium	-	-
Neutral	Observation/ absence of emotions	strong	strong	strong	-	-
Negative	Betrayal	weak	weak	weak	-	-
Negative	Frustration	medium	weak	weak	-	-
Negative	Distrust	medium	strong	strong	-	-
Negative	Insecurity	medium	medium	medium	-	-
Negative	Fear	strong	medium	medium	-	-
Negative	Manipulation	weak	weak	weak	-	-

In the positive spectrum, it is evident that Russia has strong positive sentiments in the case of 'status recognition' (essentially the acknowledgement of the actors' powerful position) and also 'expectations' (the positive evaluation of the actors' actions or even plans). In the neutral spectrum, the results are very comparable, and this is due to the fact that the neutral tweets and posts were abundant for all actors. Lastly, in the negative spectrum, one notices very comparable results with one noteworthy exception, the higher frequency for 'distrust' for the US and the EU and also the higher frequency for 'fear' as regards Russia. Furthermore, it is very important to note the low frequencies in emotions such as 'manipulation' or 'betrayal', which are much more present in countries such as Georgia and Ukraine.

Key takeaways from the BiH case study

Based on the sentimental dispositions of social media users in Bosnia and Herzegovina towards the five actors, EU, US, Russia, China and Turkey, we can advance two insights: the first one is the domination of negative sentiments towards the three actors with most references in the posts (Russia, US and the EU), something which raises a bigger question regarding the dispositions of country's public towards international actors and secondly, the relatively more positive disposition for Russia compared to the EU and the US.

Moldova

In Moldova, with a population currently standing at 3.0 M, Facebook users are estimated at 63% and X users at 5% (144.3 K) (World Population Review 2025). According to recent data, there appears to exist a clear majority of female users in Facebook (56.3% for female and 43.7% for male users), whilst the age groups of younger adults are very dynamic (18-24 years: 19.5%, 25-34 years: 22.7% and 35-44 years: 20.7%) (NapoleonCat 2025). As regards X, the data that pertain to the platform's ad reach indicate that the overwhelming majority of users are male (75% for male and 25% for female) (Kemp 2026). The country report on Moldova was prepared between late August and early September 2025. The members of the team from Moldova provided a series of hashtags that enabled the scraping and the data collection on both platforms. These were the following:

Table 22. Key terms and hashtags used for the data collection for Moldova

1. J D. Vance speech	2. Trump - Zelenskyy meeting	3. EU- defence Summit
Romanian ● #VanceMunchen ● #ConferintaDeSecuritate ● #SUAUE ● #VicepresedinteSUA #Minhen2025 **Russian** ● #ВэнсМюнхен ● #МюнхенскаяКонференция #СШАЕС ● #ВицеПрезидентСША #Минхен2025	**Romanian** ● #TrumpZelensky #CasaAlbă ● #SprijinPentruUcraina ● #SUAUcraina ● #TrumpZelensky2025 **Russian** ● #ТрампЗеленский #БелыйДом ● #ПоддержкаУкраины ● #СШАУкраина ● #ТрампЗеленский2025	**Romanian** ● #SummitUE #AparareEuropeana ● #SecuritateUE ● #ViitorulEuropei ● #CooperareMilitara **Russian** ● #СаммитЕС #ОборонаЕС ● #БезопасностьЕС ● #БудущееЕвропы ● #ВоенноеСотрудничество
In an effort to maximize data collection, we added the following search terms for all cases: "Statele Unite ale Americii", "SUA" (United States of America, USA), "Rusia" (Russia), "Uniunea Europeană", "UE" (European Union, EU), "China" (China), "Turcia" (Turkey). We also used the Russian terms for the above mentioned terms.		

The use of the hashtags in the case of X was not sufficient for the collection of a sizable sample for analysis. It was, therefore, the combination of the hashtags with other search terms that facilitated the collection. Nonetheless, it is important to note that, even with the use of supplementary search terms, the results were not as extensive as in other cases. As it will be shown, this applied particularly in the case of X. In most cases, we collected tweets (X) and posts (Facebook) written in the Romanian language, but we also collected an important number written in the Russian language that is used by part of the Moldovan population. In the case of Moldova, the number of tweets written in languages other than Moldovan (Romanian) or Russian were minimal. Subsequently, they were excluded from the analysis, given that they were not translated in a satisfactory fashion. The scraping for social media content was completed in late August and early September and it was implemented with the use of the same tools and applications found in the Apify platform that were used for the other case.

Given that the Romanian and Russian languages are also used extensively in neighboring countries to Moldova, we meticulously applied all the specifications and settings that enable the filtering of the tweets according to geographical criteria. In an overwhelming majority, most tweets came from the capital of the state, Chișinău as well as Bălți and Tiraspol. In relation to Facebook posts, we made the effort to establish an enlarged group of news organizations, media and blogs, in order to be able to collect numerous posts. Accordingly, the selection aimed- in principle- at including media that are active on Facebook and that relate to different political orientations. Still, our basic priority was the collection of an adequate volume of posts and from various sources. In the case of Moldova, we collected posts from the following sources: *Moldpres, Teleradio- Moldova, Unimedia, Tv8, Nokta, Pro-Tv- Chisinau, Telegraph Moldova* and *Jurnal Tv.* In the case of Facebook, the event selected for study was the meeting between Donald Trump and Voldymyr Zelenskyy, the presidents of the US and Ukraine, an event which caused vivid online discussions and debates. The next table presents all the relevant information as regards the precise number of X tweets and Facebook posts collected and analyzed for Moldova.

Table 23. The volume of social media content collected for Moldova

	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3
X	430	530	460
Facebook	-	1600	-
Total amount of tweets and posts collected: **3020**			

Overall, the figures confirm that in the case of Facebook the data collection yielded a bigger volume of data, namely posts. In the case of X, one observes a comparable amount of collected tweets across the different events. One similarity with the other countries studied is the significant number of tweets in relation to the second event, in particular the meeting between presidents Trump and Zelenskyy in the White House in late February 2025. On the other hand, a difference with other countries is the fact that in the third event studied, the EU Council on defense, there is not the same sharp decrease in the number of tweets. Nonetheless, in the case of Moldova, as it will be shown, many of the tweets collected were rather descriptive (i.e. reference to the actors only by use of the corresponding hashtag without any other comment or text), and subsequently the interpretation of these figures becomes more uncertain than in other countries where the tweets contained more pertinent text for analysis. In the following section of our report, we juxtapose the different sets of findings that resulted from our analysis and in particular: i) the total number of references analyzed per event and per actor, ii) the overall sentiment score per actor and per event and iii) the different sentiment categories per actor.

Actor Reference Distribution in the Sample of Moldova

The sum of references analyzed per actor and per event on both platforms, X and Facebook is an indication of the intensity with which social media users in Moldova discussed and commented about the different actors. These figures are the product of the creation of distinct subcorpora with the references corresponding to the actors, a quintessential aspect of the sentiment analysis that we perform. As in the other cases, in the case of Moldova, this procedure guarantees that despite the smaller number of references, the analysis will be equally reliable at least when it comes to the extraction and the scoring of the sentiment towards a specific actor.

At a different level, one must evoke the noticeable difference between the tweets and posts collected and the tweets and posts analyzed. In effect, in the case of X this can be related to the fact that many tweets did not contain a text retainable for analysis other than the reference to one of the actors (commonly in the form of the hashtag, i.e. #China). This pattern was of course detected in the other case studies as well; in the case of Facebook, one also notes the same difference; the number of posts analyzed is smaller and far inferior to the number of collected one regarding the posts collected. This relates to the scraping and data collection procedure, which essentially prioritizes the generalized extraction of comments and posts provided by Moldovan Facebook users in response to an initial post regarding the event under consideration, in this case the meeting between presidents Trump and Zelenskyy in the White House. Many comments do not contain any type of explicit reference to the actors and thus the analysis focused only on those that did. With the next set of results, we provide insights as regards the general sentiment score per actor for the period under study.

Table 24. Total amount of references to the actors and per event in the Moldovan dataset

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3	
Russia	**72**	**81**	**62**	***35%***
US	**46**	**79**	**33**	***25%***
EU	**83**	**62**	**81**	***37%***
China	**4**	**3**	**2**	***2%***
Turkey	**2**	**2**	**1**	***1%***
Total amount of references analyzed for X: **613** Total amount of tweets and posts collected: **3020**				
Facebook				
Russia	**-**	**193**	**-**	***40%***
US	**-**	**218**	**-**	***44%***
EU	**-**	**68**	**-**	***14%***

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
China	**-**	**4**	**-**	***1%***
Turkey	**-**	**3**	**-**	***1%***
Total amount of references analyzed for Facebook: **486** Total amount of tweets and posts collected: **3020**				

The statistical data indicate both notable similarities and also important differences with trends and patterns regarding the other country studies. A significant difference is that we don't detect a progressive decrease towards the end of the period studied. Another difference is that the EU is the actor that dominates in the quantity of references analyzed for X. This is the first case with such a configuration. In all the other cases, the EU came third with a very important difference from the US and Russia. According to our sample, this shows that in Moldova there was a steady interest to discuss the EU, something which resulted in a much more balanced distribution of the references to the three actors. The third difference is that the number of tweets for most actors (US, Russia and the EU) does not fluctuate or drastically shift from event to event, except for a small increase in number of tweets for the US and Russia regarding the second event (meeting in the White House) and decrease in the third (EU summit). Important similarities concern the distribution of references on Facebook, where one finds the US and Russia concentrating the bulk of the references. They are followed by the EU's more limited number and lastly the very limited number for China and Turkey.

Sentiment Results from the sample of Moldova

Table 25. General sentiment score per actor in the Moldovan dataset

x	Positive	Negative	Neutral
Collection period	14/2- 14/3		
Russia	**10%**	**57%**	**33%**
US	**16%**	**38%**	**46%**
EU	**53%**	**16%**	**31%**
China	**25%**	**-**	**-**
Turkey	**-**	**-**	**-**
Facebook			

x	Positive	Negative	Neutral
Collection period	28/2- 6/3		
Russia	**17%**	**51%**	**32%**
US	**21%**	**34%**	**45%**
EU	**17%**	**32%**	**51%**
China	**-**	**-**	**-**
Turkey	**-**	**-**	**-**

The following patterns are discernable in the sentiment disposition towards the actors. First, the negative dispositions are more dominant in both X and Facebook. In the case of X, the most negative sentiment is towards Russia with a significant margin between the negative and the positive sentiment (57% for negative and only 10% for positive, thus a difference of 47 points). The pattern for the US is also mostly negative but with a smaller margin between negative and positive (38% negative and 16% positive, difference of 22 points). Lastly, the outlook for the EU is the exact opposite from the one for Russia. The EU received an overwhelmingly positive score and a very low negative score (53% for positive, 16% for negative, margin of 37 points). As it was already mentioned, the small amount of data collected, leads one to regard these results with a necessary precaution. They can be considered as indications of a probable tendency within the sample collected.

In the case of Facebook, the results are partially different. The outlook for Russia and the US continues to be predominantly negative. The positive scores are slightly more significant but always with a difference from the negative (the difference between negative and positive is 34 points in the case of Russia and 13 points in the case of the US). The key difference is that the EU's outlook in Facebook is clearly negative (32% negative and 17% positive, difference of 15 points). It is certainly a notable shift from the outlook on X. More broadly, it could be argued that Russia's negative score, which was the highest and also comparable on both platforms, was frequently linked with the perception of Russia as an aggressor against Ukraine.

In the case of the US, the score in Facebook was also negative but with a smaller gap between positive and negative, one clearly sees the impact of the meeting between presidents Trump and Zelenskyy, which seems to have provoked intense affective reactions. These trends are very present on X and they are also present on Facebook, with the difference that on the latter one finds a much more frequent positive sentiment for Russia and President Putin as well as the US and President Trump.

Event Specific Shifts in the Moldovan dataset

Table 26. Sentiment scores per actor and per event in the Moldovan dataset

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
Collection period	14/2- 14/3			
Russia	**Neg.: 61%**	**57%**	**53%**	**(-8)**
	Pos.: 12%	**11%**	**8%**	**(-4)**
	Neut.: 27%	**32%**	**39%**	**(+12)**
US	**Neg.: 32%**	**45%**	**39%**	**(+7)**
	Pos.: 13%	**11%**	**23%**	**(+10)**
	Neut.: 55%	**44%**	**38%**	**(-17)**
EU	**Neg.: 18%**	**12%**	**19%**	**(+1)**
	Pos.: 48%	**58%**	**54%**	**(+6)**
	Neut.: 34%	**30%**	**27%**	**(-7)**
China	-	-	-	-
	-	-	-	-
	-	-	-	-
Turkey	-	-	-	-
	-	-	-	-
	-	-	-	-

The remarkable stability in the outlooks of the three actors (US, Russia and the EU) across the three analysed events suggest a more stable sentimental disposition. Another argument in favor of such an interpretation is the detection of recurring margins between positive and negative dispositions throughout the period and for all three actors. There are some alterations, but they hardly modify the outlook. For instance, in Russia's case there is a progressive and steady decrease of negative dispositions throughout the period (from 61% to 57% and finally to 53%). But there is also a progressive, yet smaller, decrease in the positive dispositions (from 12% to 11% and finally to 8%). This indicates a negative outlook of Russia. In the case of the U.S. there are stronger signs of a fluctuation that relate to the sequence of events. In the middle of the period, and following the meeting between presidents Trump and Zelenskyy, there is a sharp increase in negative dispositions (from 32% to 45%) and a very minimal decrease in positive dispositions (from 13% to 11%). However, towards the end of the period there is a relative decrease in the negative dispositions (from 45% to 39%) and an important increase in positive dispositions (from 11% to 23%). The general outlook is clearly negative but not as much as Russia's.

Lastly, in the case of the EU, one notes a very stable and strongly positive outlook (very low negative and neutral dispositions lower than the positive). This view was unaffected by the specific events examined by our study. As it was already mentioned, the sample for X in Moldova presents the specificity of being rather limited and thus our findings should be weighted accordingly and taken as indications of a probable tendency. In the following table we present the mapping of the different emotions associated with the actors.

Sentiment families in the Moldovan dataset

Table 27. The families of sentiments per actor in the Moldovan dataset

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Positive	Status Recognition	low	low	low	-	-
Positive	Expectations	low	low	medium	-	-
Positive	Hope/Optimism	low	low	medium	-	-
Positive	Security	low	low	low	-	-
Positive	Similarity/Affinity	low	low	low	-	-
Positive	Trust	low	low	medium	-	-
Neutral	Confusion/ uncertainty	low	low	low	-	-
Neutral	Dissociation	low	low	low	-	-
Neutral	Indifference	low	low	low	-	-
Neutral	Observation/ absence of emotions	medium	medium	medium	-	-
Negative	Betrayal	low	low	low	-	-

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Negative	Frustration	low	low	low	-	-
Negative	Distrust	medium	medium	low	-	-
Negative	Insecurity	low	low	low	-	-
Negative	Fear	medium	low	low	-	-
Negative	Manipulation	medium	medium	low	-	-

As it was already noted, in the case of Moldova the sample size is more limited. This also affected the mapping of the different categories of sentiment. This explorative aspect is founded upon the detection and the quantitative account of a big number of specific terms that fall into each of the different sentiment categories. The smaller volume of social media content made the mapping more difficult. In the case of China and Turkey we did not obtain any results, while in the other cases we obtained more substantial, yet sporadic, results.

For instance, it is very indicative that we find no 'strong' signaling in any sentiment category. The 'medium' score for the EU in the positive sentiment category (for expectations, hope and trust) in many tweets and posts are related with the EU integration prospect for Moldova. A recurring pattern presents the EU as a democratic choice that could potentially protect Moldova from the influence of actors such as Russia. On the contrary, for the US and Russia, the positive tweets and posts could not be associated with such sentiments. They mostly carried positive connotations for the actors and not necessarily for the relations between Moldova and the actors. In the case of the US, frequent patterns focus on the security guarantees for Moldova if it maintains a close cooperation. For Russia the positive dispositions seem to gravitate around themes of historical ties and Russia's capacity to counterbalance Western hegemony. In the case of the EU, negative dispositions often stress internal divisions and the strong dependence on the US when it comes to decisive action. Russia and the US obtained more 'medium' scores for negative sentiments (distrust, fear and manipulation for Russia and distrust and manipulation for the US). However, in a more qualitative dimension, the negative dispositions are quite different. For the US, the negative includes criticism for its cynicism, its destabilizing policies for smaller states and its control over the EU. For Russia, the negative seems to be more existential, as it includes the themes of aggressivity, expansionism and the threat to Moldovan sovereignty. Given the limitations of the sample, it is important to stress that this is only a tentative interpretation of probable tendencies and not a confirmation of generalized trends and features in the dispositions of the Moldovan general public towards the actors.

Key takeaways from the Moldovan case study

Our study on Moldovan social media users' sentimental dispositions towards major international actors yielded several key remarks despite the more limited sample. The first one is that the EU received a very positive score only on X, whilst it received a mostly negative score on Facebook. Russia and the U.S. have more negative scores on both X and Facebook. This is a feature that can be linked with the disappointment, the agony and the pessimism of the Moldovan public, as this was encapsulated by our study within its limits- towards international affairs and the role of the major protagonists. The second key remark relates to the similarities of the findings on both platforms, especially for Russia and the US. This shows that the negative sentiment- particularly for Russia- is quite embedded. About the US the smaller margins between negative and positive can be linked with the events of the period of study- two of which regarded directly the US- something that shows that the public's sentiments were affected by a certain interpretation and disapproval of the actors' policies.

Ukraine

Ukraine, the country with the biggest population (39 M), is also the one with the smallest shares for Facebook users (20.6 M: 53%) and X users (1.5 M: 4%) (World Population Review 2025). With regard to Facebook, there is an overwhelming majority of female users (58.4% for female and 41.6%for male users), whilst the most dominant age group is that of 25-34 years (23%), followed by those of 35-44 years (22%) (NapoleonCat 2024). On the basis of X's ad audience, it appears that 62% is male and 38% is female (Kemp 2025). The report on Ukraine was prepared and concluded during the month of July and early August 2025. The hashtags provided by the Ukrainian team of the Geo-Power-EU project enabled extensive research as regards X. The following table contains the corresponding terms.

Table 28. Key terms and hashtags used for the data collection for Ukraine

1. J D. Vance speech	2. Trump - Zelenskyy meeting	3. EU- defence Summit
#МюнхенськаКонференція #ВенсМюнхен #СШАЄвропа Relevant hashtags in English #MSC2025 #VanceSpeech #MunichSecurityConference	#трампзеленський #ПровалПереговорів #ZelenskyTrumpMeeting #TrumpMeetingZelensky ##ZelenskyTrumpTalks #TrumpZelenskyMeeting #trumpzelensky ZelenskyInWashington	#StandWithUkraine #UkraineEU #РазомзЄС #СлаваУкраїні #ReArmEurope
In an effort to maximize data collection, we added the following search terms for all cases: "США", "Америка", "Трамп", "Венс", "Росія", "Китай", "Європа", "ЄС", "Туреччина"		

In most cases, our searches yielded results and content (posts on Facebook and X) written with the Cyrillic alphabet, which is the most standardized and common form. There were very few cases of posts, mainly on X, that originated with users from Ukraine and were written in a Romanized form (Latin alphabet). The translation of these posts proved more difficult with the use of the DeepL service, therefore they were not included in the data translated and analyzed. In total, these posts were roughly one hundred in a full amount of several thousand posts; in other words, the fact that they were not included had minimal to no effects on the analysis. In the case of Ukraine, we applied the same procedure about social media scraping and data collection from X and Facebook. Evidently, the amount of the posts, particularly on X, was significantly higher than in the other countries. This applies to both the search based on hashtags as well as the terms such as the name of the international actors and their leaders. The Apify platform provided the opportunity to include geolocation parameters and to collect posts that come from users residing in Ukraine. This procedure proved reliable, something which becomes apparent based on the quantity of the collected data. In particular, the instruments used on Apify safeguard that the overwhelming, almost absolute, majority of posts will belong to Ukrainians living in the country and using the Ukrainian language and to a lesser extent the Russian language. Nevertheless, we detected a few cases where the author of a post lives in Ukraine but uses a language other than Ukrainian or Russian (i.e. Swedish, German or Italian) but also includes some terms or phrases in Ukrainian. Such posts were very rare and commonly their translation was not completed. They were left out of the translated data bound for analysis.

When it comes to Facebook, the procedure was modified, in the sense that we had to prepare an enlarged sample of Ukrainian news blogs and news media in order to maximize the collected data. We focused on media active on Facebook, in the sense that they publish stories and posts relating to the events that are of interest for our study. However, Ukraine is different to the other countries studied, given that it is a country at war, drastically affected by the policies of the actors (US, Russia and the EU, and China and Turkey). In other words, in Ukraine's case the international and the national aspect of these events are heavily intermingled. We were able to collect Facebook posts, and more importantly the comments, from the following sources: *Obozrevatel*, *Укрінформ (Ukrinform)*, *УНИАН* (*Unian)*, *Українська правда (Ukrainska Pravda)* and *РБК-Україна* (*Rbc)*. In the case of Facebook, our focus was on the second event, namely the meeting between Presidents Trump and Zelenskyy in the White House on 28 February 2025. The following table provides the exact figures with regard to the total number of tweets and posts collected and analyzed for Ukraine.

Table 29. The volume of social media content collected for Ukraine

	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3
X	4900	3600	2500
Facebook	-	2300	-
Total amount of tweets and posts collected: **13300**			

Based on this data, one can formulate the following remarks and assumptions: firstly, the amount of the collected data surpasses significantly the corresponding ones pertaining to the other countries, something which could be attributed to the much bigger population of Ukraine as well as the dramatic circumstances experienced by Ukrainian citizens, spawning public discussions. Secondly, it is observable that the two first events, the speech of US vice President JD Vance at the Munich Conference and the meeting between presidents Trump and Zelenskyy were much more discussed and commented on than the EU summit in early March. This appears to be a common trait across all studies. The following section of this report presents the different categories of findings on the basis of our analysis: i) the total number of references analyzed per event and per actor, ii) the overall sentiment score per actor and per event and iii) the different sentiment categories per actor.

The number of references pertaining to each actor in the context of the specific events and sub-periods provides an understanding of the intensity with which the social media users in Ukraine discussed and expressed their view regarding the actors.

Table 30. Total amount of references to the actors and per event in the Ukrainian dataset

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3	
Russia	**3170**	**1050**	**1400**	***36%***
US	**3600**	**1750**	**1000**	***41%***
EU	**800**	**700**	**500**	***14%***
China	**700**	**200**	**300**	***8%***
Turkey	**100**	**60**	**50**	***1%***
Total amount of references analyzed for X: **15380** Total amount of tweets and posts collected: **13300**				
Facebook				
Russia	**-**	**320**	**-**	***26%***
US	**-**	**580**	**-**	***48%***
EU	**-**	**150**	**-**	***13%***
China	**-**	**90**	**-**	***8%***
Turkey	**-**	**60**	**-**	***5%***

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Total amount of references analyzed for Facebook: **1200** Total amount of tweets and posts collected: **2300**				

In the case of X, there is a progressive decrease in the number of tweets for all actors posted from the beginning of the analysed period towards its end. The only exception is Russia; in effect, one notes that it is the only actor for which more tweets were posted in the third period in comparison to the second. Additionally, in the case of X, it is evident that the references that were analyzed were more than the tweets collected. This is because many tweets contained, rather frequently, many references to more than one actor. Our methodological approach dealt with this occurrence by creating distinct datasets for each actor. Thus, a tweet containing a reference to Russia, the US and the EU may be scored and analyzed three times. Beyond this methodological aspect, this shows the correlation between the actors in the perception of the public and social media users and especially in public discussions and debates. Frequently, the two actors jointly discussed were the US and Russia.

On the contrary, in the case of Facebook, the total number of references analyzed is significantly inferior to the total amount of the posts collected. This is directly related to the procedure of data collection and social media scraping via Apify. In the case of X, the results that we obtained depended on the detection of specific hashtags and search terms. Thus, this meant that all the tweets collected had to contain the terms in question. On the contrary, in Facebook, the instrument that we used collected all comments in an indiscriminate manner; in effect, many comments did not contain any reference to the actors. However, we did manage to collect an important number of references for the analysis.

When it comes to the distribution of the collected and analyzed references per actor, the findings clearly show that the US has been the most discussed and commented among the actors (41% on X, 48% on Facebook). Russia follows with 36% on X and 26% on Facebook. It seems reasonable to support that the important number of references to the US is the direct result of the involvement of the country's high-ranking officials in the two first events. However, it is noteworthy that the US and Russia were much more discussed also during the third sub-period which regarded the EU summit. The EU comes third with 14% on X and 13% on Facebook. China and Turkey were the least commented on or more generally mentioned. China, however, was much more present in both Facebook and X than Turkey.

Sentiment Results from the sample of Ukraine

Table 31. General sentiment score per actor in the Ukrainian dataset

x	Positive	Negative	Neutral
Collection period	14/2- 14/3		
Russia	**5%**	**50%**	**45%**
US	**7%**	**42%**	**51%**
EU	**33%**	**19%**	**48%**
China	**21%**	**25%**	**54%**
Turkey	**51%**	**9%**	**40%**
Facebook			
Collection period	28/2- 6/3		
Russia	**6%**	**48%**	**46%**
US	**8%**	**47%**	**45%**
EU	**40%**	**22%**	**38%**
China	**25%**	**25%**	**50%**
Turkey	**48%**	**10%**	**42%**

There are overwhelmingly negative dispositions towards both the US and Russia, in contrast with the strongly positive disposition towards the EU and the somewhat mixed disposition towards China and positive disposition towards Turkey. In the case of X, there is a clearly negative reaction vis-a-vis the US and Russia. In both cases, there is a very important margin between the negative and the positive scores (for Russia: 50% negative and 5% positive and for the US: 42% negative and 7% positive). The two actors also received an important sum of neutral score; however, this is very frequently the result of tweets that simply describe a development without the use of terms and more generally a vocabulary that evaluates and interprets the policies of the actors. China, presents a rather mixed or balanced outlook with minimal to no margin between the positive and the negative dispositions on both platforms (on Facebook it has the same score, 25% positive and negative, on X, the negative is slightly superior with a margin of 4 points, 25% for negative and 21% for positive). One could argue that the analyzed data indicate an oscillation between positive and negative in both platforms. When it comes to Turkey, there is a strongly positive disposition on both platforms (on X with a margin of 42 points: 51% for positive and 9% for negative).

Event Specific Shifts in the Ukrainian dataset

The following table presents the findings that illustrate the evolution of the sentimental dispositions throughout the period of study. These results help us in determining the fluctuations of all dispositions (negative, positive and neutral) and thus explore the extent to which the events of the period affected the dispositions towards the actors from the standpoint of Ukrainian social media users.

Table 32. Sentiment scores per actor and per event in the Ukrainian dataset

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
Collection period	14/2- 14/3			
Russia	**Neg.: 51%**	**53%**	**46%**	**(-5)**
	Pos.: 5%	**5%**	**4%**	**(-1)**
	Neut.: 44%	**45%**	**50%**	**(+6)**
US	**Neg.: 42%**	**43%**	**40%**	**(-2)**
	Pos.: 8%	**6%**	**7%**	**(-1)**
	Neut.: 50%	**51%**	**53%**	**(+3)**
EU	**Neg.: 23%**	**19%**	**17%**	**(-6)**
	Pos.: 30%	**36%**	**35%**	**(+5)**
	Neut.: 47%	**45%**	**48%**	**(+1)**
China	**Neg.: 25%**	**22%**	**30%**	**(+5)**
	Pos.: 20%	**18%**	**25%**	**(+5)**
	Neut.: 55%	**60%**	**45%**	**(-10)**
	Neg.: 9%	**8%**	**9%**	**(0)**

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
Turkey	Pos.: 51%	49%	53%	(+2)
	Neut.: 40%	43%	48%	(+8)

Overall, the most stable outlook pertains to Russia and the US for which there is minimal difference in sentiments from the beginning to the end of the period. The negative disposition dominates, the positive is also stable and constantly very low and the neutral appears to remain at the same levels. There are some minor fluctuations. In concrete terms, the data indicate the categorical and invariable perception and sentimental positioning of the Ukrainian citizens towards the two actors. Given that Russia's negative score is even more significant, it would be safe to assume that even prior or following this period, one might expect similar results. In the case of the US, it is evident that the two first events affected gravely the disposition of Ukrainians towards it.

On the contrary, in the case of the EU the positive dispositions are constantly more significant than the negative ones and there is progressive increase of the margin between them. In the beginning of the period (JD Vance speech) the positive dispositions were leading by 7 points, whilst in the middle of the period (Trump Zelenskyy meeting) and the end of the period (the EU Summit on defence) the margin increases to 13 and 14 points. Thus, there is a very clear and simultaneous improvement of the positive dispositions and a drop in negative dispositions. As it was already mentioned, when it comes to China, the most distinguishable pattern is the steady predominance of negative sentiment but with a very small margin from the positive (both grew up steadily from the beginning of the period to its end). Also, it is noteworthy that China was associated with the most important neutral score (60%, in the aftermath of the Trump- Zelenskyy meeting). Lastly, in the case of Turkey, despite the much more limited data collected, the pattern seems very stable. The negative dispositions are constantly low, whilst the positive ones are steadily high. The outlook is definitely positive without fluctuations throughout the period, something which could indicate that it could bear similar characteristics prior or even after this particular period.

Sentiment families in the Ukrainian dataset

The next set of findings will allow us to explore the various connections between the actors and a series of distinct emotions. These results are based on the relative frequency of a specific set of keywords that relate to the emotions that we defined a priori.

Table 33. The families of sentiments per actor in the Ukrainian dataset

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Positive	Status Recognition	medium	medium	medium	weak	weak

Positive	Expectations	weak	medium	medium	weak	weak
Positive	Hope/Optimism	weak	weak	medium	weak	weak
Positive	Security	weak	weak	weak	weak	weak
Positive	Similarity/Affinity	weak	weak	medium	weak	weak
Positive	Trust	weak	weak	weak	weak	weak
Neutral	Confusion/ uncertainty	medium	medium	weak	weak	weak
Neutral	Dissociation	weak	weak	weak	weak	-
Neutral	Indifference	weak	weak	weak	weak	-
Neutral	Observation/ absence of emotions	strong	strong	medium	weak	weak
Negative	Betrayal	strong	medium	weak	weak	-
Negative	Frustration	medium	medium	medium	weak	weak
Negative	Distrust	strong	medium	weak	weak	weak
Negative	Insecurity	strong	medium	weak	weak	-
Negative	Fear	weak	weak	weak	weak	weak
Negative	Manipulation	medium	weak	weak	weak	-

The results are very helpful in our effort to map the dynamics of the sentimental dispositions among Ukrainian social media users. Our mapping establishes that across all data the negatively charged terms are the most common. Arguably, this highlights the impact that the war has had on the Ukrainian citizens' understanding of international matters and more precisely and the policies and positions of the international actors. If we focus on the actors' profile, it is observable that the US and Russia seem to share the most similarities across all three different categories. They appear to be the least associated with positive sentiments. The difference is that Russia is more intensively associated with negative sentiments than the US. In the group of negative sentiments, Russia is the one with the highest frequency or intensity (betrayal, distrust and insecurity) with the US also receiving 'medium' scores in almost all variations of negative sentiments. For Russia, common themes in the negative pole include the notion of invasion, aggression, the atrocities of its war action and in general a threat to Ukraine's existence as a country. In the case of the US, the negative dispositions are commonly associated with the perception of insufficient or declining support and its emphasis on self- interest. In the group of positive sentiments both the US and Russia received a 'medium' score for status recognition, which in effect is a way to measure all the references that alluded to their power and leverage in international affairs. The US got a 'medium' score with regard to expectations but in all other cases both countries were very weak on positive sentiments. In the group of neutral dispositions, the scoring of both countries is almost identical, with a notable finding being their 'medium' score in uncertainty.

The EU has a very different pattern. Firstly, in the positive spectrum, it is noteworthy that it received a similar score with regard to status recognition. Secondly, it received 'medium' scores in expectations, hope and similarity. Certainly, in no case did it receive a ‘strong’ result, but it did, however, obtain a much more positive reaction than the US and Russia. Commonly, the themes associated with the positive disposition include the perception that the EU can help Ukraine with modernization and post-war reconstruction as well as the strengthening of democracy. Furthermore, it received a much weaker score in the negative spectrum with frustration being assessed as ‘medium’. Recurring patterns in this regard include the idea that the EU’s procedural protocol is complex and ineffective, resulting in less decisive actions compared to the US. Lastly, it is important to add the dimensions of China and Turkey, despite the smaller sample. For China, the positive sentiment includes the themes of its potentially important role for the economic reconstruction of Ukraine in the post-war period and to a lesser extent its capacity to act as a mediator. On the other hand, the negative sentiment includes the theme of its ambiguous (approving) stance towards Russia and its aggressive and destructive policies. Turkey is quite often presented as an important ally of Ukraine, particularly in terms of the military equipment that it provided but in the more negative aspects it is criticized for its balancing policies and avoidance not to take sides in relation to the war.

Key takeaways from the Ukrainian case study

The study on the social media platforms in Ukraine allowed us to obtain a systematic view of the sentimental disposition towards the five actors. The US and Russia, who have dominated the discussions and debates on X and Facebook, received a very clearly negative score. Russia’s negative score was the most important (50%) but in both cases the element that validated this outlook was the very important margin between positive and negative dispositions (45 points in both cases). This means that the expression of the Ukrainian X and Facebook users was rather categorical and unequivocal, leaving very little elements of doubt. In effect, both countries had very weak positive scores (below 10%). Moreover, in both cases it was obvious that the sentimental dispositions were stable throughout the period. The EU received a clearly positive score (33%) with an important margin from the negative (14 points). Furthermore, EU’s positive and negative scores developed in a contrasted pattern (the positive grew stronger and the negative became weaker). Although the positive score was not overwhelming (33%), our analysis indicates that the events of this period- particularly the meeting the American and the Ukrainian presidents at the White House- may have had a significant effect in the increase of positive sentiment for the EU. Lastly, it is important to note the rather mixed score of China (positive and negative in equal share) and the overwhelmingly positive score of Turkey.

Georgia

In the case of Georgia, a country with a population of 3.8 M, one finds the most impressive percentage of Facebook users with a massive 95% (3.7 M), whilst the percentage of X users are quite comparable to the numbers available for the other countries (216.3 K: 6%) (World Population Review 2025). In the case of Facebook, it is noteworthy that there is a majority of female users (53.7% for female and 46.3% for male); moreover, the age group 25-34 years was the largest (approximately 28%) (NapoleonCat 2025). As regards X, data pertaining to the ad audience indicate that male users make up for about 70% and female users for 30%, percentages which are very comparable to those noted for the other countries included in our study (Kemp 2025). The report on Georgia was compiled during the month of August 2025. The Georgian team participating in the Geo-Power-EU project provided a series of hashtags which facilitated the task of scraping and data collection on X. These were the following:

Table 34. Key terms and hashtags used for the data collection for Georgia

<table>
<tr><th>1. J D. Vance speech</th><th>2. Trump - Zelenskyy meeting</th><th>3. EU- defence Summit</th></tr>
<tr>
<td>• #მიუნხენისუსაფრთხოებისკონფერენცია #MiunkhenisUsafrtkhoebisKonferentsia (#MunichSecurityConference)
• #მიუნხენისკონფერენცია#MiunkhenisKonferentsia(#MunichConference)
• #უსაფრთხოებისკონფერენცია2025 #UsafrtkhoebisKonferentsia2025(#SecurityConference2025)
• #ჯეიდივენსი#JeidiVensi (#JdVance)
• #ჯდვენსი #JDVensi (#JDVance)
• #14თებერვალი2025 #14Teberevali2025 (#14February2025)
• #ვენსიმიუნხენში #VensiMiunkhenshi (#VanceInMunich)</td>
<td>• #ტრამპიზელენსკი #TrampiZelenski (#TrumpZelenskyy)
• #ზელენსკიტრამპიშეხვედრა #ZelenskiTrampiShekhvedra (#ZelenskyyTrumpMeeting)
• #ტრამპიზელენსკითეთრისახლი#TrampiZelenskiTetrisSakhli (#TrumpZelenskyyWhiteHouse)
• #ზელენსკიაშშში#ZelenskiASHSHshi (#ZelenskyyInUSA)
• #28თებერვალი2025#28Teberevali2025 (#28February2025)
• #თეთრისახლი2025 #TetrisSakhli2025 (#WhiteHouse2025)</td>
<td>• #ზელენსკიევროკავშირში #ZelenskiEvrokavshirshi (#ZelenskyInEU)
• #ზელენსკი6მარტი #Zelenski6Marti (#Zelensky6March)
• #ევროსამიტი2025 #EvroSamiti2025 (#EUSummit2025)
• ევროსამიტი#EvroSamiti (#EUSummit)
• #საგანგებოევროსამიტი#SagangeboEvroSamiti (#EmergencyEUSummit)
• #საგანგებოსამიტი #SagangeboSamiti (#EmergencySummit)
• #ევროკავშირისსამიტი#EvrokavshirisSamiti (#EUSummit)</td>
</tr>
<tr><td colspan="3">In an effort to maximize data collection, we added the following search terms for all cases: “ამერიკის შეერთებული შტატები” (United States of America), “რუსეთი” (Russia), “ევროკავშირი” (European Union), “ჩინეთი” (China), “თურქეთი” (Turkey)</td></tr>
</table>

In many cases, the search for relevant content on X through hashtags did not yield a significant amount of results. However, the combination of the hashtags with other key terms, such as the name of the international actors, did facilitate the detection and subsequently the scraping of a substantial amount of data. Furthermore, we were able to collect tweets (X) and posts (Facebook) predominantly written in the Georgian language. We also collected a very small number of posts and tweets written in Russian. As in other cases, we did detect a very minimal number of tweets that were written in languages other than Georgian. We included these tweets in the analysis only in the cases where the translation was satisfactory. Such tweets were very rare; thus their inclusion or rejection did not alter the character of the final sample. In all cases, the specifications regarding the search parameters enabled the filtering and the retention of the content that was published by social media users residing in Georgia. Quite understandably, the most dominant location was Tbilisi, the capital of the country. With regard to the scraping of Facebook posts, our goal was to establish a pool of news media, news blogs and sites that are very active when it comes to publishing stories regarding major international news. Furthermore, the effort was made to include several media that are closer- from a political standpoint- to both the government and the opposition viewpoints. Accordingly, we collected more than 2000 posts and comments from the following sources: *Rustavi2*, *Netgazeti, Kavkasiatv, Imedi, FormulaTV, 1TV and Mtavari Arkhi.* About the content from Facebook, the event that was used as a landmark for scraping was the meeting between Donald Trump, the US president, and Volodymyr Zelenskyy, the president of Ukraine, in the White House in late February 2025. The following table contains all the relevant information as regards the precise number of X tweets and Facebook posts collected and analyzed for Georgia.

Table 35. The volume of social media content collected for Georgia

	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3
X	610	1150	380
Facebook	-	2180	-
Total amount of tweets and posts collected: **4320**			

The data indicate the following: firstly, the total number of tweets and posts collected are comparable to the countries with the exception of Ukraine. Secondly, it is observable that the meeting between presidents Trump and Zelenskyy spawned the most intense discussions and arguably reactions and debates- about X users- among the three events during the period of interest. In effect, the EU summit, in early March, drew the weakest attention among X users. In the next part of our report, we present the distinct groups of findings that relate to our analysis, namely: i) the total number of references analyzed per event and per actor, ii) the overall sentiment score per actor and per event and iii) the different sentiment categories per actor.

Actor reference distribution in the Georgian dataset

The different categories of findings are the result of the analysis of the X tweets and Facebook posts that relate to the five international actors. In particular, the findings refer to the quantity of references that pertain to each actor during each of the three events of the period studied. This quantitative aspect informs on the intensity with which the social media users in Georgia participated in discussions and debates regarding the actors.

Table 36. Total amount of references to the actors and per event in the Georgian dataset

x	J.D. Vance speech (14 February)	Trump- Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Total
Collection period	14/2- 27/2	28/2-5/3	6/3- 14/3	
Russia	**190**	**310**	**105**	***35%***
US	**250**	**320**	**115**	***40%***
EU	**170**	**90**	**50**	***18%***
China	**25**	**22**	**28**	***5%***
Turkey	**20**	**15**	**13**	***2%***
Total amount of references analyzed for X: **1723** Total amount of tweets and posts collected: 4320				
Facebook				
Russia	**-**	**370**	**-**	***49%***
US	**-**	**230**	**-**	***31%***
EU	**-**	**115**	**-**	***15%***
China	**-**	**20**	**-**	***3%***
Turkey	**-**	**14**	**-**	***2%***
Total amount of references analyzed for Facebook: **749** Total amount of tweets and posts collected: 4320				

The findings indicate that, in the case of X, the volume of tweets about Russia and the US increased in the second event (Trump- Zelenskyy meeting) and then decreased in the third event (EU summit). In the case of the EU there is a steady decrease in the number of tweets throughout the period. The small number of tweets for China and Turkey makes it riskier to evoke a clearly discernible pattern. Another noteworthy finding pertains to the number of tweets and posts analyzed compared to the total number of tweets and posts collected. Thus, in the case of X, it is observable that the two figures are somewhat close (1723 analyzed for 2140 collected).

The difference stems from the fact that many tweets contained references to the actors that were of minimal to non-existing analytical value, such as the use of a hashtag with the name of an international actor (i.e. #Russia) but not in the context of a phrase or a proposition containing a more developed meaning. In other cases, which were smaller in number, the name of the international actor was found in tweets that regarded different fields and topics of interest, unrelated to our study, namely domestic news like the economy, culture and sports. In the case of Facebook, there is a significantly more sizable margin between the total number of posts analyzed compared to the total number of posts collected (749 analyzed and 2180 collected). The difference relates to the different procedure of scraping and data collection used on the Apify platform, already explained in the previous country studies. Furthermore, many comments regarded Ukraine without any reference to the other actors. Thus, it was difficult for us to include them in our analysis in a methodologically consistent and meaningful fashion.

The second important parameter of this general assessment of the quantitative aspects of the data analyzed regards the number of references analyzed per actor. In broad terms, it is clear that we detect three distinct patterns: i) the US and Russia were the actors with the most significant and comparable amount of references in both X and Facebook, ii) the EU held an intermediary position and iii) China and Turkey were present in a small number of tweets and posts (5% and below) with China appearing more frequently than Turkey. As in other country studies, the US and Russia appear to be evoked very frequently in the same tweet or post, whilst the EU tends to be evoked more often individually. Also, many of the references to the US and Russia include explicit references to their respective leaders, which is not the case for the EU.

Sentiment Results from the sample of Georgia

The following table provides the results when it comes to the overall sentiment score for all actors and for both platforms.

Table 37. General sentiment score per actor in the Georgian dataset

x	Positive	Negative	Neutral
Collection period	14/2- 14/3		
Russia	**15%**	**42%**	**43%**
US	**17%**	**35%**	**48%**

x	Positive	Negative	Neutral
EU	**26%**	**34%**	**40%**
China	**15%**	**30%**	**55%**
Turkey	**40%**	**15%**	**45%**
Facebook			
Collection period	28/2- 6/3		
Russia	**16%**	**56%**	**28%**
US	**11%**	**50%**	**39%**
EU	**19%**	**43%**	**38%**
China	**13%**	**52%**	**35%**
Turkey	**32%**	**40%**	**28%**

There are overwhelmingly important scores for the negative disposition across all actors and on both platforms, particularly on Facebook. Only Turkey has a positive score that is higher than its negative score. On X, Russia and the US obtained a clearly negative outlook: Russia: 42% negative and 15% positive (margin of 27 points), US: 35% negative and 17% positive (margin of 18 points). The sentimental disposition towards Russia is more negative on Facebook (56% with a margin of 40 points from positive views, 16%); the US also had an even more negative score than the one on X (50% with a margin of 39 points from the positive views, 11%). The EU also received a negative score. However, the margin between negative and positive disposition is weaker on X (34% negative, with a margin of 8 points from positive, 26%) than on Facebook (43% negative, with a margin of 24 points from positive, 19%).

China's outlook is equally more negative on Facebook than on X, but with very important margins on both platforms (15 points for X and 39 points for Facebook). Lastly, Turkey is the only case with a contrasting result. With regard to X, Turkey received a very positive score (40% and only 15% negative). On the other hand, it received a negative score on Facebook (40% with 32% for positive).

In attempting to interpret the overall sentiment score in a more comparative aspect and also with some degree of consideration for the recurring arguments and views found in the positive and the negative poles, we could formulate the following remarks: firstly, it seems that Russia's negative score is linked with views and evaluations that surpass the events of the specific period. This applies to both platforms, since very frequently the negative sentiment towards Russia is linked with the war in which it was implicated against Georgia (2008) and the war against Ukraine. There are also frequent negative dispositions as regards the perceived alignment of the US with Russia against

Ukraine. In the case of the US, the negative views seem to be connected more frequently with the events of this particular period and especially the meeting between presidents Trump and Zelenskyy in the White House. In the case of China and Turkey, the limited number of references prevents us from attempting to interpret the sentiment scores in a more qualitative manner.

Event specific shifts in the Georgian dataset

The following table provides a more detailed presentation on the evolution of the sentiment scores for all actors according to the succession of the events that our study takes as reference points.

Table 38. Sentiment scores per actor and per event in the Georgian dataset

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
Collection period	14/2- 14/3			
Russia	Neg.: 40%	54%	33%	(-7)
	Pos.: 13%	17%	17%	(+4)
	Neut.: 47%	29%	50%	(+3)
US	Neg.: 29%	47%	29%	(0)
	Pos.: 24%	12%	16%	(-8)
	Neut.: 47%	41%	55%	(+8)
EU	Neg.: 41%	28%	36%	(-5)
	Pos.: 27%	26%	24%	(-3)
	Neut.: 32%	46%	40%	(+8)

x	J.D. Vance speech (14 February)	Trump-Zelenskyy meeting (28 February)	EU-Defence Summit (6 March)	Fluctuation from first to last event
China	**Neg.: 36%**	**28%**	**26%**	**(-10)**
	Pos.: 13%	**15%**	**18%**	**(+5)**
	Neut.: 51%	**57%**	**56%**	**(+5)**
Turkey	**Neg.: 13%**	**12%**	**16%**	**(+3)**
	Pos.: 38%	**40%**	**42%**	**(+4)**
	Neut.: 49%	**48%**	**42%**	**(-7)**

There seems to be the lack of a consistent and clearly discernible pattern throughout the period. The second event (the meeting between presidents Trump and Zelenskyy in the White House) did seem to provoke an intense sentimental reaction for most actors, however not to an extent that would lead us to detect a shift or an intensification of an existing pattern. For instance, in the cases of Russia and the US, it is clear that the developments in the White House caused a strong increase in negative views but not in a way that affected the general outlook in a deeper way. The same counts for the EU. With regard to Russia, in particular, the increase in negative views was reversed towards the end of the period, whilst there was even a slight increase in positive views. Certainly, the general outlook remained predominantly negative, but it seems that there was a correction in the end of the period, as if the increase of the negative views was somewhat incidental.

When it comes to the US, there is a similarly sharp increase in the negative views but towards the end of the period the negative views returned to the level prior to the events in Washington. However, in this case the positive views decreased at the end of the period and, thus, one could evoke a considerable shift of the pattern and the outlook. In simple terms, it seems that the speech by JD Vance and the meeting in Washington led Georgian social media users to view the US less positively.

As regards the EU, the fluctuations indicate rather minor shifts. This seems to concern mostly the negative views which were relatively decreased towards the end of the period (with a sharp decrease in the middle of the period). The positive views were also slightly decreased and, therefore, it is hard to evoke a shift in the outlook. As it was already mentioned, the EU presents a negative outlook as well (when comparing negative and positive) but with lower margins of difference. In any case, our data do not suggest that there was a major correlation between the negative for the US and Russia and the positive for the EU. When it comes to China, there is a shift towards more positive and less negative dispositions towards the end of the period. It is very indicative that China also presents the highest portion of neutral dispositions. Turkey's outlook remained steadily very positive. It was, in effect, the most positive and the least negative throughout the period.

Sentiment families in the Georgian dataset

The following table presents the results that illustrate our effort to map the ways in which the different actors were associated with a series of different sentiments. These results rely on a quantification of occurrences of relevant keywords, but the main objective is to detect patterns of similarities and differences among the actors and not to provide a systematic measuring.

Table 39. The families of sentiments per actor in the Georgian dataset

Sentiment	Category	**Russia**	**USA**	**EU**	**China**	**Turkey**
Positive	Status Recognition	Strong	Strong	Medium	-	Weak
Positive	Expectations	Medium	Medium	Medium	Weak	Weak
Positive	Hope/Optimism	Medium	Medium	Strong	-	Weak
Positive	Security	Weak	Weak	Weak	-	-
Positive	Similarity/Affinity	Weak	Weak	Weak	-	-
Positive	Trust	Weak	Weak	Medium	-	-
Neutral	Confusion/ uncertainty	Medium	Medium	Weak	Weak	Weak
Neutral	Dissociation	Weak	-	Weak	-	-
Neutral	Indifference	-	-	-	-	-
Neutral	Observation/ absence of emotions	Strong	Strong	Medium	Weak	-
Negative	Betrayal	Strong	Medium	Weak	-	-
Negative	Frustration	Medium	Medium	Medium	-	Weak
Negative	Distrust	Strong	Strong	Medium	Weak	-
Negative	Insecurity	Medium	Medium	Medium	Weak	Weak
Negative	Fear	Strong	Strong	Medium	-	Weak
Negative	Manipulation	Strong	Weak	-	-	-

The US and Russia are the two actors with the "strongest" occurrences across all three categories, "positive", "neutral" and "negative". The EU is in an intermediary position with many more "medium" occurrences than China and Turkey which present mostly "weak" occurrences and also present a lack of frequencies in several sentimental categories. In a more detailed consideration, we remark that the US and Russia are almost identical in the positive category: they are the only ones with a very "strong" score when it comes to status recognition which essentially attest to the perception of many social media users that the two actors can influence the outcome of major developments. Both actors present fewer occurrences relating to hope and expectations, whilst they both present very few occurrences for security, similarity and trust. In the case of the US, in the positive category there is a frequent reference to the guarantees that it can offer to Georgia regarding its Euro-Atlantic aspirations. In the category of neutral dispositions, they are also almost identical, with a key similarity regarding the "strong" score on the category "observation-absence of emotions".

The similarities between US and Russia are also important in the negative pole, with some differentiations. Russia presents the most frequent occurrences about "betrayal" and "manipulation", while both actors have also very frequent occurrences relating to "fear" and "distrust". In effect, this configuration can be very likely linked with the troubled history of Russia-Georgia relations as well as the analogies that many Georgians drew between the terrible fate of Ukraine at the hands of powerful actors and the experience of their own country. In the case of the US, recurring patterns for the negative sentiment include the themes of insufficient support for Georgia and its hesitation to fully confront Russia to the benefit of countries like Georgia.

In the case of the EU, despite the smaller number of references, we have clearly a different pattern. The EU presents a more frequent occurrence of "hope" and "trust" compared to Russia and the US, particularly with regard to the economic and political benefits (rule of law and democracy) of closer ties. Thus, it is observable that the EU marks the lowest score on "betrayal" and also lower scores in "fear" and "distrust". This indicates a different quality of negative sentiments. As it was already mentioned, the EU's negative score relates frequently to its being perceived as weaker than the US and Russia or lacking the will to uphold its promises towards countries such as Ukraine and even the idea that it is an actor that will eventually avoid confrontation to protect its interests. This is very different from being perceived as an actor that harms and causes destruction. In the case of China and Turkey the very small number of references analyzed does not allow for a more categorical interpretation of the scores.

Key takeaways from the Georgian case study

The first major finding about the sentimental dispositions of Georgian social media users towards the five international actors relates to the overwhelmingly negative sentiment towards most actors and especially those who were most frequently discussed, namely Russia, the US and the EU. Certainly, the EU had more positive and less negative reactions than Russia and US, but still the general outlook was negative. This applies also to China but not to Turkey. The preponderant negative sentiment found on both platforms could be a sign of the frustration, disappointment and pessimism of social media users as regards international actors and their impact on Georgia. The second important remark regards the probable correlation of the events studied on the negative feeling towards the actors, primarily Russia and US, and also the EU. In that respect, it seems that the turbulent meeting between presidents Trump and Zelenskyy did cause an increase in the negative dispositions towards the US and Russia but not throughout the period. Moreover, the negative sentiment towards Russia, which is the most intense, seems to be less connected with the developments in Washington. The sentiment towards the EU did become more positive and less negative but without a shift that overturns the domination of negative over positive.

Comparative overview and discussion

Sum of X tweets and Facebook posts analyzed per actor

We begin this presentation with the more descriptive parts of our studies, namely the number of references analyzed per actor on X and Facebook. It is important to clarify that by references, we essentially point to the number of sentences referring to the different actors in X tweets and Facebook posts. Therefore, these results inform us, in essence, on the volume of tweets and posts per actor.

Table 40. The percentages regarding the amount of references analyzed in X per actor in the period between 14 February to 14 March 2025 (For BiH it applies only for the period between 28 February and 6 March 2025)

Region	Country	EU	US	Russia	China	Turkey
Western Balkans	Serbia	20%	25%	46%	7%	2%
	North Macedonia	30%	36%	24%	6%	4%
	Bosnia & Herzegovina	18%	26%	42%	5%	9%
Average (WB)		**23%**	**29%**	**37%**	**6%**	**5%**
EaP	Ukraine	14%	41%	36%	8%	1%
	Moldova	37%	25%	35%	2%	1%
	Georgia	18%	40%	35%	5%	2%
Average (EaP)		**23%**	**35%**	**35%**	**5%**	**2%**

In the case of X, the mean percentages for all actors are very similar in the two regions. The US and Russia are commonly found in the first two positions and the EU in the third, whilst China and Turkey in the fourth and the fifth. The only difference is the bigger mean percentage for the **US in the EaP countries** and the biggest percentage for **Russia in Western Balkan countries**. Overall, Russia and the US are the most discussed actors. However, there are intra and extra regional variations in this regard. In the Western Balkans, Russia's position is particularly high in Serbia and also Bosnia and Herzegovina. In the EaP countries, the US position is particularly high in Ukraine and Georgia. The EU's highest percentages are found in Moldova and North Macedonia.

Table 41. The percentages regarding the number of references analyzed in Facebook per actor in the period between 28 February to 6 March 2025 (For BiH it applies for the whole period between 14 February to 14 March 2025)

Region	Country	EU	US	Russia	China	Turkey
Western Balkans	Serbia	14%	49%	32%	3%	2%
	North Macedonia	20%	43%	32%	3%	2%
	Bosnia & Herzegovina	24%	37%	36%	2%	1%
Average (WB)		**19%**	**43%**	**33%**	**3%**	**2%**
EaP	Ukraine	13%	48%	26%	8%	5%
	Moldova	14%	44%	40%	1%	1%
	Georgia	15%	31%	49%	3%	2%
Average (EaP)		**14%**	**41%**	**38%**	**4%**	**3%**

As regards the results from Facebook, it is important to take into account that for most cases (with the exception of Bosnia), the results apply only to the meeting of President Trump and Zelenskyy. From this standpoint, it becomes easier to explain the strong domination of the US in both regions and especially in the Western Balkans. On the other hand, it is clear that in both regions the EU's position remains stable (3rd after the US and Russia) but with decreased percentages. Thus, the results from Facebook help us to complete the patterns detected in X. It is confirmed that the EU is in an intermediary position, the US and Russia continue to occupy the two first positions, whilst China and Turkey have a minimal presence.

The sentiment score

Table 42. Net sentiment balance on X (Twitter) (Positive %- Negative%) including the percentage of neutral

Region	Country	EU	US	Russia	China	Turkey
Western	Serbia	-21	+2	-6	+13	+18

Region	Country	EU	US	Russia	China	Turkey
Balkans		29%	30%	28%	10%	18%
	North Macedonia	-16 40%	-14 46%	-10 40%	+20 40%	+8 42%
	Bosnia & Herzegovina	-14 42%	+9 47%	+2 42%	+19 53%	+40 38%
Average (WB)		**-17** **37%**	**-1** **41%**	**-5** **37%**	**+17** **34%**	**+22** **33%**
EaP	Ukraine	+14 48%	-35 51%	-45 45%	-4 54%	+42 40%
	Moldova	+37 31%	-22 46%	-47 33%	-	-
	Georgia	-8 40%	-18 48%	-27 43%	-15 55%	+25 45%
Average (EaP)		**+14** **40%**	**-25** **49%**	**-40** **40%**	**-6** **55%**	**+22** **43%**

Overall, the results from X across both regions and all countries, indicate a rather active expression of opinion and more importantly sentiment. In effect, the mean percentage of neutral sentiment is 41%, something which indicates that almost 60% of the tweets are oriented towards a specific sentiment. The expression of sentiments is somewhat more polarized in the EaP countries (-40 to +22), whilst it is narrower in the Western Balkan countries (-17 to +22). Furthermore, if one takes into account the sentiment score per country and per region, a series of notable differentiations arise firstly, the sentiment towards the EU is predominantly negative in the Western Balkans, whilst it is inversely clearly positive in EaP countries (with the exception of Georgia). The sentiment towards the US and Russia in the Western Balkans is also somewhat balanced (almost neutral for the US, slightly negative for Russia). On the contrary, in the EaP countries, both actors received a predominantly negative score, particularly Russia. Lastly, it is noteworthy that Turkey has also received a consistently positive score across both platforms.

Table 43. Net sentiment balance on Facebook (Positive %- Negative%) including the percentage of neutral

Region	Country	EU	US	Russia	China	Turkey
Western Balkans	Serbia	-17 17%	-12 22%	+10 28%	+13 10%	+18 18%
	North Macedonia	-31 27%	-7 47%	+16 36%	+42 28%	-2 20%
	Bosnia & Herzegovina	-23 39%	-26 38%	-9 35%	+12% 56%	-19 33%
Average (WB)		**-24** **28%**	**-15** **36%**	**+6** **33%**	**+22** **31%**	**-1** **24%**
EaP	Ukraine	+18 38%	-39 45%	-42 46%	0 50%	+38 42%
	Moldova	–15 51%	-13 45%	-34 32%	-	-
	Georgia	-24 38%	-39 39%	-40 28%	-39 35%	-8 28%
Average (EaP)		**-7** **42%**	**-30** **43%**	**-39** **35%**	**-13** **28%**	**+10** **23%**

The findings from Facebook indicate a rather active discussion when it comes to expressing sentiment towards most of the actors. In particular, the mean percentage of the neutral dispositions is around 33%, at even lower levels than that in X. Also, the polarization of sentiment expression is once stronger in the EaP countries (-39 to +10, compared to -24 to +22 in the Western Balkan countries). The scoring pertaining to the actors also contains similarities and differences in comparison to the results from X. In effect, in the case of the Western Balkan countries, the EU and the US received an even more negative score. However, Russia received a positive score on Facebook (negative on X), particularly in Serbia and North Macedonia but not Bosnia and Herzegovina. In the EaP countries, the results are quite similar when it comes to Russia and the US (both very negative in all countries) but differ in relation to the EU which received a negative score on Facebook. It was less negative than the one noted for the Western Balkan countries but mainly due to the very positive score it received in Ukraine. Lastly, China received a positive score in the Western Balkans and a negative one in EaP countries and Turkey a more positive score in the EaP countries. However, as we have stressed already, the significantly fewer data that we collected for the two countries makes it more difficult to insist on such comparative results.

Cross-tabulation based on co-occurrence

The final set of comparative results that we present are those that emanate from a series of cross-tabulations that we run only on specific parts of the datasets containing the sentiment scores. In particular, for each country, and subsequently for the two regions, we decided to focus on the part of the scored data (X tweets and Facebook posts) that contain references to more than one actor and in particular the three actors with most references, US, Russia and EU (possible combinations for co-occurrence: Russia-EU-US, US-EU, US-Russia, Russia- EU). Accordingly, the pairwise cross-tabulations were performed on the multi-actor tweets and posts in order to examine the ways in which the sentiments towards one actor co-varied with sentiments toward the other. We applied the Cramer's V coefficients in order to obtain a measure of the strength and the direction of association between sentiment distributions. By this procedure, we were able to identify elements of alignment, namely mild, weak or even absent co-dependence. The first table contains the corresponding data for the Western Balkan countries.

Table 44. Results of cross-tabulation on social media post from Western Balkan countries

Country	Russia- US	Russia- EU	US-EU	Scoring Patterns
Serbia	0.22	0.12	0.13	The neutral - neutral co -occurrence is the most dominant (30%), low association and EU independence
North Macedonia	**0.42**	0.32	0.21	Higher co- dependence, Negative-Negative and Positive- Positive (50-60%) especially for Russia- US
Bosnia and Herzegovina	**0.41**	0.23	0.06	Also high co-dependence and partly inverse. Negative- Negative, Positive- Positive for Russia- US and Negative-Positive for Russia -EU

This table summarizes the results of cross-tabulation analysis on the basis of the already existing sentiment scoring in Serbia, North Macedonia and Bosnia and Herzegovina. The values represent the level of association between the sentiment patterns towards Russia, the EU and the US. Across all three countries, the strongest and most consistent relationship is the one between Russia and the US, meaning that the sentiments towards them seem to be moving more frequently in the same direction. In Bosnia and Herzegovina and in North Macedonia this pattern regards both the Positive- Positive and the Negative-Negative trend. In Serbia such associations are weaker. Overall, the EU appears to be the least connected actor, meaning that the sentiment towards it presents itself as more independent and also rather negative. The following table presents the exact same data for EaP countries.

Table 45. Results of cross-tabulation on social media post from EaP countries

Country	Russia- US	Russia- EU	US-EU	Scoring Patterns
Ukraine	**0.34**	0.23	0.16	The most common pattern is the Neutral- Neutral and also Negative-Negative and Positive- Positive for US- Russia
Moldova	**0.37**	**0.43**	0.28	The co- dependence can be described as moderate to strong. The most common patterns include the Negative- Negative for Russia- US and also the partially inverse Negative (Russia)- Positive (EU)
Georgia	**0.33**	0.26	0.18	The alignment can be described as moderate. Among the most common is the Negative- Negative for Russia- US. The EU pairs are the weakest

Based on the cross-tabulation results, it appears that in all countries of the Eastern Partnership, the association between Russia and the US is the strongest and the most consistent. Quite commonly, the scoring pattern is the alignment in the negative sentiment. The Russia-EU pair is clearly weaker in terms of frequency and in a considerable part of the scored sample it reflects a partial opposition (Negative for Russia and Positive for the EU). The EU-US pair shows the weakest and least stable connection, whilst it is dominated by neutral co- occurrences. Overall, the two regions present several similarities with the EU being the actor with the most independent patterns for sentiment distribution. In plain terms, this means that the sentiments for the EU are not affected as much by the sentiments towards the other actors.

Concluding remarks

This report provided a detailed description of the sentiment analysis performed in relation to social media users' (X and Facebook) affective dispositions towards the following five international actors, the EU, US, Russia, China and Turkey in three countries of the Western Balkans: Serbia, Bosnia and Herzegovina and North Macedonia and three countries of the Eastern Neighborhood (Ukraine, Georgia and Moldova). The analysis was conducted according to the premises and specifications of NLP. The results consist of a quantification of these affective dispositions. As it was already mentioned, the analysis and its findings focus on the empirical aspects; in other words, the main objective was to provide a series of results that are verifiable and meaningful in terms of comparison.

The empirical outcomes of our study have successfully identified specific patterns across the six countries and the two regions as well as the social media platforms. Overall, it is clear that the negative sentiments dominate, particularly for the three main actors (EU, US and Russia) on both platforms and the two regions. This is for instance the case for the EU, with the exception of the results from X in the EaP countries. It is also the case for the US and even more so Russia. In Russia's case the exception comes from the results pertaining to Facebook in regard to the Western Balkan region. China and Turkey were associated with more positive and neutral dispositions; however, the much smaller datasets force us to formulate this remark with precaution. Certainly, the predominance of the negative sentiments is an element that merits special attention since it may be linked with a more general sentiment of disappointment, frustration and pessimism from the general public.

In our effort to look deeper into the associations between the sentiment patterns for the actors, we did manage to establish that the sentiment towards the EU is not only negative but also the most independent since it does not follow the changing patterns of the other actors. On the contrary, the two sentiments that seem to be co-dependent are those of the US and Russia. Arguably, this trend may be linked with the period and the events studied. However, given that we examined the social media content during an entire month, we estimate to have gathered a representative sample when it comes to detecting distinguishable patterns. Our measurement was dynamic and not static. We fully acknowledge all the limitations (methodology, period, platforms, uneven data volume) but on the other hand, we believe that we proceeded through reliable steps. In that respect, it is our conviction that the report will contribute to other major objectives of the GEO- POWER- EU project.

The empirical contribution of this report facilitates the formulation of a series of remarks that relate to several policy and analytical implications. A first element regards the importance of studying and analyzing sentimental dispositions regarding geopolitics. It is important to stress that affective dispositions and tone do not and cannot coincide or be identified with rationally extracted opinions and views, such as the answers to surveys or semi-structured interviews. Sentiment analysis deals with the dynamics of discussion and debate as they take place in real time. The affective dispositions reveal a variety of sentiments such as trust, fear, hostility, expectations or admiration among others, that are at times expressed simultaneously and co-exist within the margins of a single post or tweet. Certainly, a negative opinion carries potentially negative sentiments; however, our study showed that there are many nuances. In the period of one month, we recorded shifts from event to event and from one platform to another. We also documented different margins between the basic sentimental categories of positive, negative and neutral. In six different countries we recorded six distinct frameworks of sentimental expression. All these elements can complement and enhance the interpretation of the findings of surveys and even discourse analysis studies. A sentiment analysis offers many opportunities and perspectives than a mere corroboration or rebuttal of the findings of a survey. It provides an additional window of reflection that may capture ongoing transformations and dynamics that are not explicitly stated or covered by a series of given queries.

A second element relates to the capacity of sentiment analysis of geopolitics to reveal the fragmentation of public opinion. Our empirical data indicate noteworthy differences between the countries, the two regions, WB and EaP, and between the platforms. This general trend leads to the acknowledgement of the risks of using one source or case study when it comes to the interpretation of multilayered phenomena and processes linked with geopolitics. Our study cannot provide an interpretation or an explanation as to why the EU received so negative reactions in the WB countries under study and more positive reactions in EaP countries. The same counts for the more mixed reactions towards US and Russia in the WB countries and the overwhelmingly negative reactions in EaP countries. Also, this study cannot explain why China and Turkey are commonly viewed more positively but also less frequently discussed. However, by focusing on producing solid empirical findings we have laid a steppingstone for redesigning a survey or fine tuning a study on manipulated information. This also includes the opportunity to link the empirical data of this study with broader research interests and questions regarding the quality of democracy and media freedom in the countries under study or even the media coverage of geopolitics and the major actors. Certainly, this also includes the ability to compare different periods and monitor the shifts across a variety of events.

Subsequently, this study and the report that encapsulates its dimensions carry the potential of improvements and adjustments, particularly the inclusion of a machine learning component, in order to broaden the scope and the content of analysis (i.e. several geopolitical actors, several countries, several social media platforms and lengthier periods of time). Sentiment analysis can contribute significantly in monitoring reactions to geopolitics without rushing to judgment or battle with a priori and the predispositions that are inevitably inherent to the expression of opinion or the question that provokes it. This monitoring tool serves to enrich not compete sound methodologies such as surveys.

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