Comparing Narratives and Discourses in the Russo-Ukrainian War

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Abstract

This study investigates the different narratives and discourses surrounding the Russo-Ukrainian war. We collected four datasets from Russian and Ukrainian news articles and Telegram channels. We used various tools for analyzing the datasets: TF-IDF, Aspect-based sentiment analysis and sentiment analysis. Our results showed that discourses in Russian news articles focused on law, state, national politics and American politics, whereas Ukrainian news had a tendency to focus on events and developments of the war. For Russian Telegram channels, their discourses focused on the situation of the war rather than the impact, while the Ukrainian Telegram channels had a more demeaning and opinionated language towards the Russians.

Additionally, we found significant differences in sentiment for certain aspects between Russian and Ukrainian Telegram messages and news articles. Our findings suggest that there are notable differences and similarities in discourses between the two sides of the conflict. By analyzing these media platforms we wanted to gain further insight into what discourses and narratives the Russian and Ukrainian populations are exposed to through their news. Future studies could investigate the extent to which media influences the opinions of the Russian and Ukrainian public.

Keywords: *Russo-Ukrainian war, NLP, news articles, Telegram.*

1. Introduction (TK)

The Russo-Ukrainian war has drawn significant international attention and concern ever since its beginning in 2014 (Shah & Gedamkar, 2022). The conflict, which has been argued to have its roots from decades earlier, has resulted in thousands of deaths and has displaced even more people (Kuzio, 2021). This has especially been escalating ever since the invasion of Ukraine in February 2022. As the conflict continues to go on, it might be interesting to look into how the discourse about the war differs between Russia and Ukraine. Especially how the Russian news and social media portrays the war, compared to the Ukrainian news and social media, might shine light onto the differing and similar perspectives of the two countries.
That is why in this study we want to investigate the differences and similarities in the discourses and narratives, between the Russian Ukrainian news-sources, from the beginning of the Russian invasion of Ukraine in February 2022. Furthermore, we want to investigate the potential impact on the Russian and Ukrainian population. For this research, we applied natural language processing algorithms on scraped data from news sites and Telegram channels from both countries. In order to make this comparison we utilized Aspect-Based Sentiment Analysis (ABSA) to create four aspect-datasets from where we could identify some key-aspects of interest, and compare the sentiment towards these aspects between Russian and Ukrainian news sources. Furthermore we applied TF-IDF on the aspects-datasets in order to identify unique occurrences of aspects in the respective datasets. Lastly we used a bag-of-words sentiment analysis approach to compare the general sentiment over time of the two countries. This has been done in order to get a better understanding of the differences and similarities of the ways in which the conflict is being described by these two nations. This could potentially lead to a better understanding about how the population of the two nations might be persuaded into different beliefs about the war.

Other studies about the language utilized when referencing the Russo-Ukrainian war have been made. In a study made after the invasion of Ukraine, Hanley et al. (2022a) researched the spread of misinformation utilizing a toolkit of different Natural-language-Processing

(NLP) tools, with scraped data from Russian news sites. They found that several misinformation narratives were spread across all of the scraped websites, and that certain websites were responsible for setting up certain misinformative narratives. In another study closely related to ours, Hanley et al. (2022b) utilized another toolkit of NLP tools, to make a quantitative comparison between the narratives spread by the Russian, Western and Chinese media. They found that each of these groups had entirely different and nuanced perspectives. Yet there hasn't been a direct comparison between the discourses of the Russian and the Ukrainian media.

As we are conducting exploratory research, we do not have any prior assumptions about any possible findings in our research.

2. Methodology and Materials (SM)

As a popular source of information for individuals of both countries, we chose to analyze Telegram channels (Bergengruen, 2022). By analyzing Telegram channels, we want to gain insight into the types of discourses and narratives that are present in this informal media platform.

In total, we collected data from four sources: Two for both Ukrainian and Russian news sites and two for both Ukrainian and Russian Telegram channels.

To collect data we used a variety of tools including web scraping, API's and different Python packages. For analyzing the data we used aspect-based sentiment analysis, sentiment analysis and TF-IDF. In the following section the research design will be explained in further detail.

2.1 News articles. (SM)

The study consisted of collecting data from six news sites: three Russian (sputniknews.com, rt.com and tass.com) and three Ukrainian (kyivindependent.com, kyivpost.com and tsn.ua).

The amount of articles scraped can be seen in table 1.

Ukrainian and Russian news sites

Ukrainian Media:	Number of articles:	Russian Media:	Number of articles:
kyivindependent.com	576	sputniknews.com	3,000
kyivpost.com	2,670	rt.com	258
tsn.ua	2,528	tass.com	2,999
Total:	*5,774*	*Total:*	*6,257*

Table 1: Number of articles collected by Ukrainian and Russian news sites

The focus of the data collection was on the ongoing conflict between Russia and Ukraine. To ensure we consistently collected data regarding the conflict, we used specific categories regarding the war on the news sites or specific search queries, which was only relevant to Russian news sites, where our search query was "Ukraine" (hence the different use of words for the war by Russia). A randomizer was used to gather up to 3,000 articles from each source. We utilized Python 3 (Van Rossum & Drake, 2009) and the library Newsplease (Hamborg et al., 2017) for collecting the data of the articles.

We used the python library Scrapy (Kouzis-Loukas, 2016) to parse the HTML (i.e. the structure of the website) and gather hyperlinks together with the python library Selenium (Bowen, 2020) to either scroll through the websites or go to the next page. This process is also what is referred to as web scraping (gathering information on websites such as hyperlinks) and web crawling (scrolling through webpages).

2.2 Telegram channels. (SM)

In addition to the news articles, we also collected data from Telegram using the python library Telethon (Lonami Exo, 2022) to scrape specific channels. Telethon utilizes Telegram's API, and therefore it is also required to have an API key to use the library.
A total of 106,253 messages were collected from 22 Ukrainian Telegram channels and 97,571 messages were collected from 20 Russian Telegram channels. The Telegram channels contain a variety of news sources, private individuals and groups. As most of the

Telegram channels are written in either Russian or Ukrainian, the python package googletrans (SuHun Han, 2020) was used to detect which language the message was written in and translated to English.

To gather data relevant for the research, a few criterias had to be made. Our criterias were:

- The channels should regard the war.
- We would not manually select channels to avoid any selective biases.
- We wanted to randomize the selection of the channels as much as possible.

The only source we found with a list of relevant channels for Russian Telegram channels was the "AskARussian" subreddit (FiveSleepingOwls, 2022). From here we made a list including all of the channels listed under the subreddit.

The only source we found with a list of relevant channels for Ukrainian Telegram channels was also under a subreddit called "Ukraine " (girion13, 2022). Same approach was done here with making a list including all channels mentioned on the page.

We then removed duplicated channels for both lists. To limit us from getting an excessive amount of data we filtered out channels with more than 20,000 messages.

2.3 Ethical considerations. (SM)

In this study, we only used publicly available data and ensured that our use of data was in compliance with the terms of use by the relevant websites if any terms of use were given. We followed the best practices for web crawling as those outlined by Thelwall & Stuart (2006). Furthermore, we ensured that our web crawling would not violate those terms given by the robots.txt file by the given website.

We accessed the Telegram channel messages through Telegram's API and only scraped channels open to the public.

We made every effort to maintain objectivity and tried to avoid any possible biases in our research.

2.4 Preprocessing of data. (SM)

Preprocessing of the data involved several steps. First, we removed all rows that did not contain any main text for both the Telegram channels and news articles. Furthermore, since we needed the dates the articles were published, we had to extract these for Tass, since newsplease did not fetch them. This was done using the python package requests

(Chandra & Varanasi, 2015), iterating through all of the main texts, since they contained the dates. Additionally, the dates before the war began at 03-24-2022 were removed.

To prepare the data for aspect-based sentiment analysis (ABSA), we had to separate the main text in the Telegram channels by dots and line breaks to get only the sentences. For the news articles we only separated the sentences by dots, since every time there was a line break in a news article, it would already have a dot to separate it. All of the words were also made lowercase, to make the sorting process easier.

2.5 Aspect based sentiment analysis. (SM)

ABSA (Pattakos, 2021) is a way of using sentiment analysis where instead of tokenizing each sentence and collecting a sentiment score for individual words, it utilizes the context by doing lexical analysis of a sentence by finding the adverbs and adjectives to a paired noun.

In order to identify the adjectives and adverbs paired with nouns, tokenization and lexical analysis were done by using the python package spaCy (Honnibal & Montani, 2017). In this way nouns can be located and its associated adjective and any connected adverb for each sentence. In the following sections of the paper, these nouns will be referred to as aspects.

To do the ABSA we used the python package VADER (Hutto & Gilbert, 2014) to gather the sentiment compound scores for all adjectives and possible belonging adverbs associated with a specific aspect. VADER is a lexicon of words and their connected sentiment values made from a pre-trained model. When VADER performs a sentiment analysis it outputs a positive, a negative and neutral score, and then a sentiment compound score, which is calculated from taking the sum from all positive, negative and neutral scores, and then normalizes the score ranging between -1 and 1.

The sentiment analysis was done on the translated data from the Telegram channels. For the creation of the summary, we later aggregated all of the sentiment compound values of the aspects. We then made a summary of the 10 most frequently used aspects for both the Telegram channels and news articles. Furthermore, we examined which aspects were being used frequently and selected a few key aspects, which could be interesting to investigate further in order to identify differences and similarities in how these aspects were

employed by the various sources. We conducted the non-parametric Wilcoxon rank sum test (R Core Team, 2022) on our selected key aspect in order to compare the aspects and find similarities and differences. We used the Wilcoxon rank sum test as our data was not normally distributed, but more or less had the same shape.
To remove any outliers in our key aspects we looked at the distribution of the data over time to see if there were some channels which had used the same phrases in multiple messages, which would skew our data.

2.6 TF-IDF by aspects. (SM)

TF-IDF stands for "Term Frequency- Inverse Document Frequency" (Robinson, 2022) which is a method that can be used to look at how frequent a word appears in one text compared to how frequent they appear in other texts.
The TF-IDF score is a product of the Term Frequency (TF) and Inverse Document Frequency (IDF) values (derivation can be seen in Appendix 7.1a). Words with a high TF-IDF score are considered to be of more importance to the content of the different corpuses. Since we had already found the term frequency when making the summaries of the four absa datasets, this will not be further elaborated. However, further data preprocessing had to be done in order to calculate the TF-IDF values, since spaCy (Honnibal & Montani, 2017) took emojis as aspects and also words, which had not been translated, as aspects. We filtered by words which only contained letters from the English alphabet to avoid the emojis and untranslated words. The TF-IDF scores were calculated by using the Tidytext package (Silge & Robinson, 2016) in R (R Core Team, 2022). We then arranged the scores descendingly and visualized with ggplot2 (Wickham, 2016).

2.7 Sentiment analysis over time. (SM)

For analyzing the sentiments over time, we again used the VADER package (Hutto & Gilbert, 2014) to gather sentiments for all sentences throughout the different sources. Mapping was done using the ggplot2 (Wickham, 2016) package in R using dates for the x-axis and sentiment compound values for the y-axis. The reason behind making sentiment analysis over time for this research design was to get an insight into how particular events might have shaped public sentiment.

3. Results (TK)

3.1 most common aspects for each of the four datasets (TK)

The four tables, shown in the appendix in section 7.2c, present the 10 most frequent aspects for each of our four datasets respectively. These tables give an understanding of the differences and similarities between the tables, and give an insight into what narratives are the most common amongst the four datasets.

3.2 TF-IDF over most commonly used aspects by group (TK)

Figure 1 presents a visualization of the TF-IDF scores, which showcases how unique one aspect is for the dataset compared to the other datasets. The visualization shows the 15 highest tf-idf scores for each of our four datasets.

Figure 1

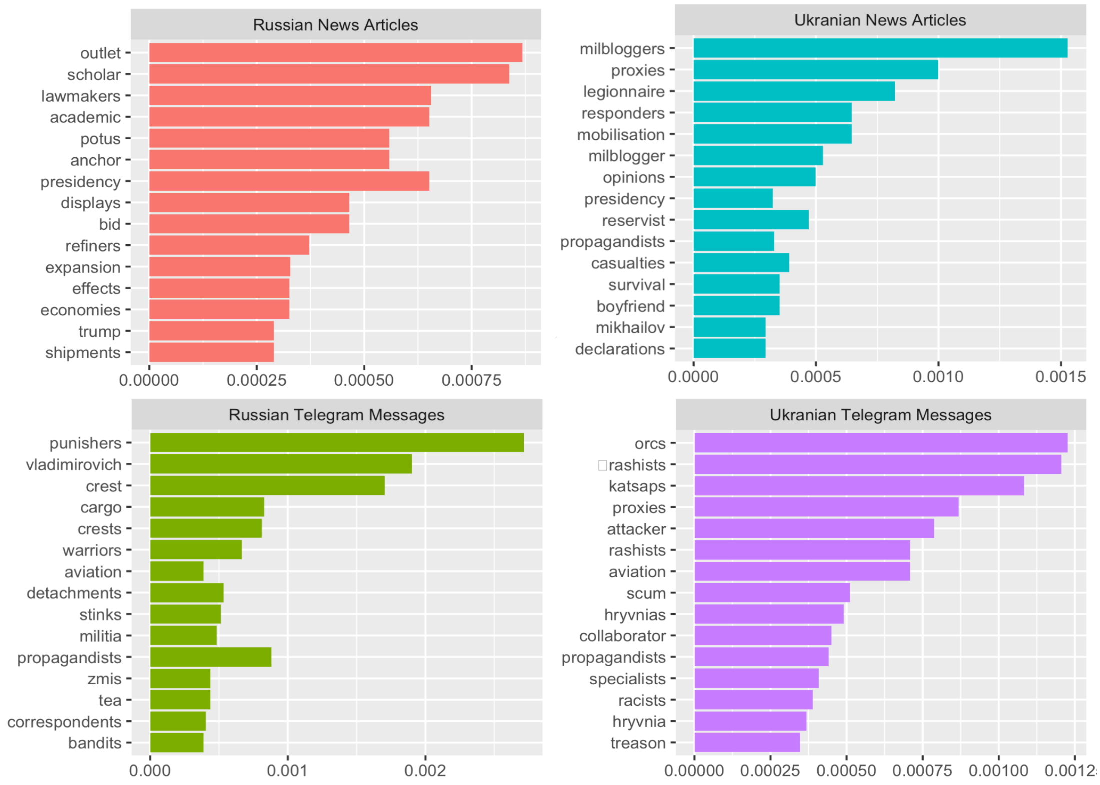

Figure 1: TF-IDF values for 15 most unique aspect terms by the four datasets

"Orcs" refers to the mythological creature that we, among other stories, see in "The Lord of the Rings" by J. R. R. Tolkien, "rashists" being a mix of the three words "Russians", "racists" and "fascists", and "Katsaps" being a word stereotyping Russians as having goatees. (Mirovalev, 2022; *Urban Dictionary*, 2011).

3.3 Results of comparison between sentiments of selected aspects (TK)

Comparison of Telegram channels (TK)

Table 7.2d shows results of the Wilcoxon rank sum test used to compare sentiment compound value, of a selected aspect, between Russian Telegram and Ukrainian Telegram channels. This is done for each of our 12 selected key aspects. The Wilcoxon rank sum test between compounds of selected aspects between Russian and Ukrainian Telegram channels, showed significant differences in the compound of the aspects: forces (p < .001), enemy (p = .008), situation (p < .001), and strikes (p = .023), as listed in the table.

Figure 2 presents the boxplots showing the compound-values of the aspects from the news sites for both Ukraine and Russia for each of the selected key-aspects. In these plots, compound values equal to zero are filtered out as they dominate the data and would make very flat boxplots with almost quartiles being zero.

Figure 2

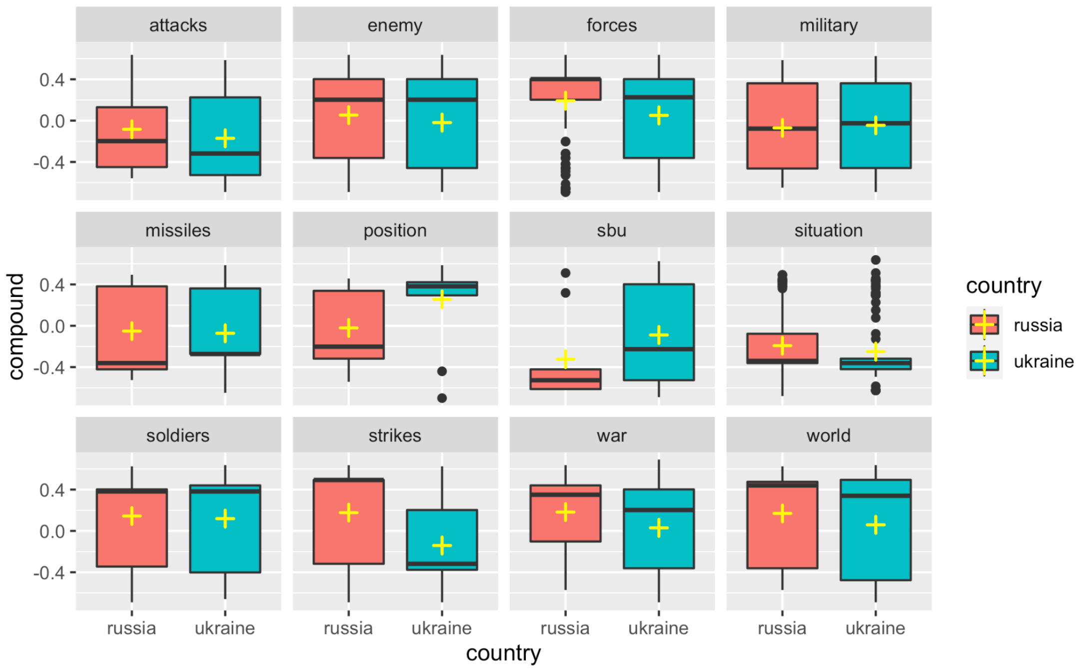

Figure 2: boxplots showing the compounds from Telegram respectively for Ukraine and Russia for each selected aspect. The yellow cross shows the mean value.

Comparison of news articles (TK)

Table 7.2e shows the results of the Wilcoxon rank sum test used to compare the sentiment compound values of a selected aspect in respectively Russian news articles and Ukrainian news articles. This is done for each of our 12 selected key aspects. The Wilcoxon rank sum test between compounds of selected aspects between Russian and Ukrainian news sites, showed significant differences in the sentiment compound of the aspects: forces ($p < .001$), enemy ($p = .008$), situation ($p < .001$), and strikes ($p = .023$), as listed in the table.

Figure 3 presents the boxplots showing the compound-values of the aspects from Telegram for both Ukraine and Russia for each of the selected key-aspects. Again, the compound values equal to zero are filtered out. Note that it does not include the aspect "sbu", as we did not have sufficient data to create a meaningful Wilcoxon rank sum test for this aspect.

Figure 3

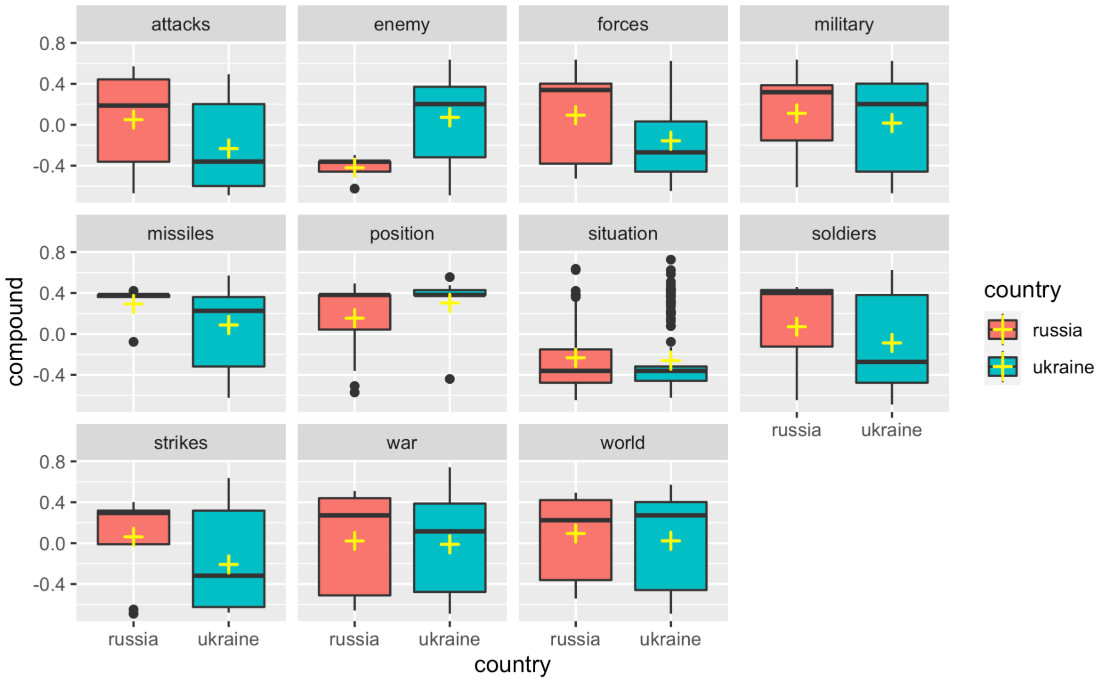

Figure 3: boxplots showing the compounds from telegram for Ukraine and Russia for each selected aspect respectively. The yellow cross shows the mean value.

3.4 General sentiment over time: (TK)

Figure 4

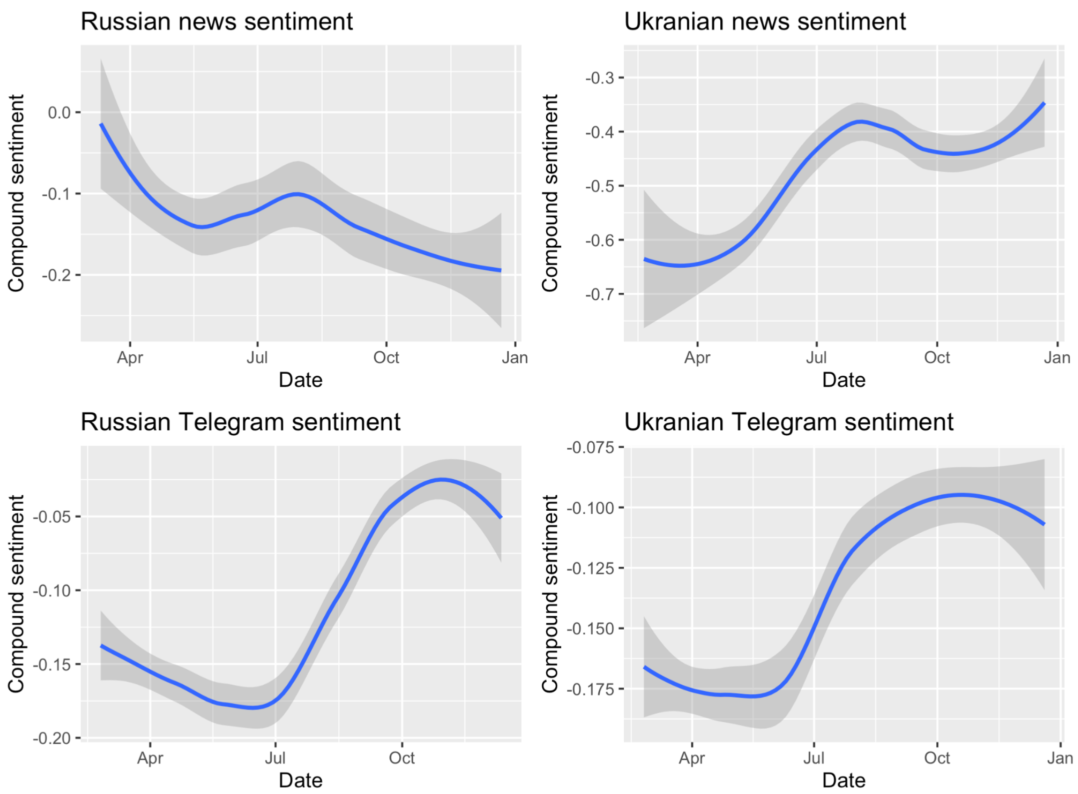

Figure 4: Graphs showing the general sentiment over time for Russian news sites, Ukrainian news sites, Russian Telegram channels and Ukrainian Telegram channels respectively.

Figure 4 presents four graphs that show the general sentiment over time respectively for our four datasets.

Looking at the Russian news sentiment, there generally was a downward trend, but with a rise in sentiment at approximately the end of july. With the Ukrainian news there generally was a big upwards going trend relative to the change in sentiment seen on the other graphs. Again, a sudden rise can be seen at approximately the end of July.

Looking at the sentiment for both of the Telegram channels, they follow similar looking patterns of sentiment over time. Though, there were some differences in timing. The Russian Telegram sentiment seemed to decline until late June, where it rose until about November where it became more steady and maybe even started to fall a bit. The Ukrainian

Telegram sentiment decreased in the chronological beginning of the graph, but then started to rise in late May or start June and then got more steady at about start-October.

4. Discussion

4.1 Summary of results (TK)

Our four summaries shown in table 1 through 4, showing the 10 most frequent aspects for each of our four datasets showed showed that there are some frequent aspects unique to each dataset, like the Ukrainian Telegram being the only one to have “sbu” and “occupiers” on its 10 most frequent aspects.
The tf-idf scores shown in figure 1 shows the aspects that are used the most in one dataset but at the same time not shown as commonly in the others.
Through testing with the Wilcoxon rank sum test for a difference in sentiment compound of the selected key-aspects between Russian and Ukrainian Telegram we found a significant difference in the following aspects: soldiers, war, forces, situation, and position. Same method applied for Ukrainian and Russian news, we found significant differences in the sentiment compound for the following aspects: forces, enemy, situation, and strikes. When looking at the general sentiment over time for all four datasets we found differences in the general trend between Russian and Ukrainian news, but we also found that the two trends between sentiment of the Russian Telegram and the Ukrainian Telegram were with few differences.

4.2 Interpretations of results (TK)

Comparing the four summaries of our datasets (TK)

The aspects that are common between the 10 most frequent aspects of the four datasets are all things you would expect to see in discourses concerning war. This is an indicator that our dataset is valid even after translation of languages.

The Russian news, judging by the summaries, seems to be the only one of the datasets to write a lot about “president”, which can be interpreted in numerous ways since we don't know whose president is being referred to, but the sentiment is dominantly positive towards “president” in the Russian news. Looking further into it, we saw that in the Russian

news, there are only few aspects referring to the actions happening on the battlefield, and instead more aspects referring to Russian politics like “diplomat”, “authorities”, “government”, “spokesman”, “countries” and ”prices”.
Looking at the 10 most frequent aspects for the Ukrainian news they seem to be mostly referring to the Russians as “invaders”.

Another observation is that Russian Telegram seems to be talking more about “media” than the others, as it is on the 10 most frequent aspects for Russian Telegram (7.2c). This might suggest a higher level of engagement to the media and news compared to the Ukrainian population.
In contrast to the Ukrainian news, the 10 most frequent aspects for Ukrainian Telegram seem to be mostly referring to the Russians as “occupiers”.
It is also worth noting that it is only the two Telegram datasets who have “enemy” as on their 10 most frequent aspects, which might point towards a more direct and informal discourse on Telegram compared to the discourse on the news, because “enemy” would be considered a more direct word to use.

The TF-IDF scores of our datasets (TK)

When looking at the TF-IDF scores (figure 1), we see some differences in the aspects that are used more frequently in one dataset but not in the others. For Russian news articles we see a lot of talking about law, state, and politics with aspects like “lawmakers”, “economies”, “trump”, “potus”, “shipments” and “expansion”, which points towards the news not really referring specifically to the situations on the battlefield of the war a lot, or what the Russians refer to as a special military operation (McDermott & Bartles, 2022). Instead they have more of a discourse about what the war/special military operation means for the country. Also aspects like “POTUS” (President of the United States) and “Trump” occurred in the TF-IDF scores for Russian news which also indicates a focus on American politics by the Russian news. This could be tied together with the study done by (Gerber & Zavisca, 2016) which showcased that in 2016, 53% of the Russian population thought America was the enemy in the conflict of the annexation of Crimea in 2014. Also In his new years speech for 2023, Russian President Vladimir Putin, proclaimed *"The West lied about peace, It was preparing for aggression ... and now they are cynically using Ukraine* *and its people to weaken and split Russia.."*, which showcases the focus Russia has on the west, which our results also suggest (Cordell, 2022).

From the Ukrainian news articles we see a more direct use of language about the war with words like “mobilization”, “casualties” and “survival”. They also seem to refer often to milblogging which, as indicated by a study, is an efficient way of dominating the information-warfare (Major, 2009).
For Russian Telegram messages we see a little more political opinion, and more direct aspects show up about the war than what we see in the Russian news articles. We see this through words like “warriors”, “bandits”, “propagandists”, “aviation” and “militia”. These words refer more to the situation of the war rather than the impact of the war, which seems more dominant in Russian news articles.
In the Ukrainian Telegram messages, we probably see the most opinionated aspects out of the four datasets. We see that they often use words like “orcs”, “rashists”, “scum”, “racists” and “katsaps” which are some demeaningly toned words that the Ukrainian population use when referring to Russians. Because of these use of words, we can point towards the Ukrainian Telegram channels thus having a very negative, subjective discourse that is targeted against Russians.

Comparison by Wilcoxon rank sum test of the Telegram channels (TK)
By comparing sentiment compounds of specific aspects between the Russian Telegram channels and the Ukrainian Telegram channels, it is quite interesting that we found a significantly more positive sentiment compound for both “soldiers", “war” and “forces” for the Russian Telegram channels compared to the Ukrainian. Although we cannot be certain whose soldiers and forces they are referring to, it might show there generally is a more positive Russian attitude to warfare. Both Russian and Ukrainian Telegram channels have a very negative sentiment about “situation”, but Ukraine has a significantly lower sentiment towards “situation”. Again we cannot infer that they are speaking of a specific situation, but it might point towards a general understanding about how two countries' populations refer to the different situations or “the” situation concerning the war. Also we see that Ukraine has a significantly higher general sentiment compound about “position”, which could be an effect of the war starting to turn a little bit since August when Ukraine

started launching counter attacks towards Russia, and they have been starting to capture back some positions since September (Bigg, 2022). Of course “position” can mean many things, and this is certainly not the aspect we have the biggest amount of data on so it would be rightful to stay critical about the significance of difference in this particular aspect.

Also we didn't find significant differences in aspects like “enemy”, “strikes”, and “missiles”. This means that both Russia and Ukraine, speak with generally similar sentiments about these things. For the aspect “enemy” this would for the most part mean the respective enemy for each country, and the fact that the two countries' Telegram channels have the same sentiment for this aspect, would imply that they generally speak in the same tone about their enemies. For “strikes” and “missiles” this could be because the Telegram messages could be referring to both their own country’s strikes and missiles as well as the other country’s strikes and missiles. This could give some more mixed sentiment values and therefore we would not see big differences in these aspects. Surprisingly we found no significant difference in the sentiment about “sbu” which is the security service of ukraine. Towards this aspect we see a generally negative sentiment of the Telegram channels between the two countries. This might be because of a low sample size from the Russian Telegram dataset of just 40 samples. It might also be from other error sources that will be further discussed in the methodological limitations section.

Comparison by Wilcoxon rank sum test of the news sites (TK)

When comparing sentiment compounds of specific aspects between the Russian and the Ukrainian news sites, we found that the aspects “forces”, “situation" and “strikes” had a significantly lower general compound value for Ukraine than for Russia. A result which corresponds with the difference we found for the comparison of the two Telegram datasets. Again, we cannot say whose “forces” and whose “strikes” is being referred to but it might give a more general overview about the news sites narratives about the warfare. When looking at the results for “situation”, we found a similar result to what was found with the Telegram channels. Both countries seem to have a generally negative sentiment about this aspect. Yet again we found a significantly lower general sentiment for Ukraine compared to Russia for “situation”. Once more we cannot say that it is a specific “situation” that is being referred to, but it might give a more general overview of the general situation and the smaller situations going on in the war. Interestingly, unlike the Telegram channels for the two countries we this time, in the news, found a significant difference in the aspect “enemy”, where we see a very negative general sentiment from Russian news, but a quite neutral general sentiment from the Ukrainian news. This might point towards the Russian news being more open about their attitude towards Ukraine than Ukraine is towards Russia. However, there might be a source of error. If Ukrainian news for example were to refer to the “enemy” as “strong” then the general compound would rise in the Ukrainian dataset, as “strong” would be considered a generally positive description by the sentiment analysis package. It is also worth noticing that we have a relatively small sample of 30 in the Russian news dataset of the aspect “enemy” which could also be a source of uncertainty.

Apart from the significant differences between the sentiment of the news aspects, there are also some insignificant differences with aspects like “soldiers”, “military”, “position”. This means that there is a general agreement of sentiment towards these aspects. It is hard to pinpoint whose “soldiers”, “military” and “position” is being referred to, as it might be a mix of the respective enemy's and the ally’s for both the Ukrainian and Russian news sites.

Interpretation of graphs showing sentiment over time. (TK)

Finally, when looking at the graphs showing the sentiment over time for our 4 datasets (figure 4), we see for the Russian news sentiment that it generally follows a downwards trend. This could, in a more generally speaking way, be a buildup of impatience for Russia. As the war goes on, Russia still can't seem to establish a completion of the goals they first set out to do (Marples, 2022). The peak in the graph we see at the end of July, might be an effect of Russian forces making some steps of progress in the war at the time. As an example The last city in the Luhansk oblast was taken over by Russia in July (Bigg, 2022).

On the opposite side of the war, we see the Ukrainian news, at the start of the Russian invasion, having a low sentiment compared to the other datasets, but then starting a general upwards-going trend. This could be an effect of the Ukrainians starting to fight back in the war. We see this especially with a sharp rise in sentiment from about mid-may peaking at about end-july. This might be as Ukraine starts having success in fighting back.

In June, Ukraine captured Snake Island which is an important position for combating the naval power of Russia (Bigg, 2022). After this in end-June or start-July, Ukraine starts gaining a little bit of momentum on the war front with help from the HIMARS missile-systems brought to Ukraine from the USA (BBC News, 2022). From August and September, Ukraine continues their momentum on the war front, while continuing to capture back important positions (Bigg, 2022). This could be the explanation of the continued rise in sentiment in the Ukrainian news. We see almost the same trend for the Ukrainian Telegram channels as we do for the Ukrainian news, but we do not see such sharp rises as we see in the Ukrainian news.

This could be an effect of news sites influencing the narratives of others, as we have seen before in the study by Hanley et al. (2022a)

For the Russian Telegram sentiment we see a similar trend to what we see in the Russian news until about July. Here the sentiment continues to rise despite the war starting to turn around towards the advantage of Ukraine, as we have argued before. There could be a number of different reasons for this. It might be that the Russian population are distracted by the government propaganda, and are not told the whole truth about how the war is going (Khaldarova & Pantti, 2016). Also there is evidence that the Russian government in recent years has been earning the population's support when invading territory (Mahaletskyi, 2020). If this is the case, then the population might be persuaded into thinking that the war is moving on towards the benefit of Russia's goals.

4.3 Implications: Why do your results matter? (TK)

Our findings contribute to a further understanding of the key differences and similarities in the discourses, between the Russian and Ukrainian news sources. This is important as it leads to a bigger understanding about how the two countries receive the news and messages presented to them. Some studies present evidence that indicates that the media might be able to, within a certain degree, facilitate the changes that they seek (MUTZ & SOSS, 1997). On the other hand, there also seems to be evidence that media can only affect “what people think about, not what they think” (Entman, 1989). But another important factor to remember is that there has been evidence showing that the media can restrict the information with which people understand issues (Happer & Philo, 2013). This could be a factor that could alter the two countries' respective public views about the war.

Therefore, our study may not only reveal how people receive the news and messages presented to them, but also to some degree how they might perceive them. This might also make sense when we look at our current understanding about social cognition about how people unconsciously learn from each other, and how humans have the ability to deceive each other (Adolphs, 2009). These traits of the human mind could invoke the strategies that might, knowingly or unknowingly, be utilized by Telegram channels or news sites to impact people's perception in the information-warfare.

4.4 Methodological limitations (SM)

Limitations by using Telegram as a source (SM)

There were several limitations involved in collecting data from Telegram channels. One of the limitations was that by scraping whole channels, some had more statistical power (Appendix 7.2a) than others due to a larger set of messages. However, since a separation between Russian channels and Ukrainian was needed, this was the preferred way of doing it. To address this limitation, we could have implemented a criterion by limiting the amount of messages per day or raising the minimum amount of messages per channel to mitigate the problem of statistical power by certain channels.

Our method of selecting Telegram channels might also have introduced a bias to our results. One potential issue of this was is stated in the study "Happenstance" (Hanley et al., 2022a, p. 8) that many newly created Reddit users started posting in the subreddit "*r/Russia*" after the beginning of the war, potentially being accounts created by the government or other actors who wanted to influence the informational warfare (Khaldarova & Pantti, 2016).

To address this limitation, it would have been ideal to obtain lists from both Russian and Ukrainian sources, as well as having Russian and Ukrainian speaking researchers to help identify the sources behind the channels. However, due to language barriers and a limited availability of sources, we were unable to do so.

Another limitation caused by the language barrier was our need for translation through the translator API. This may have introduced inaccuracies and errors caused by both the translator and cultural differences which Feng (2020, p. 101) argued that in order to accurately translate, one must be familiar with the cultural background contained in the language.

It is also argued by Sherstoboeva (2020, p. 93) that Russians do not have online freedom of expression in accordance with the CoE legal standards and that Russia also has an intricate surveillance system and excessive control over online media. This would imply that our data of Russian news-sources, in some cases, would not completely express the actual political position of the publishers.

Limitations by using news sites (SM)

While it would have been optimal to select a larger number of news sites and reduce the sample size for each news site, we encountered difficulties scraping the hyperlinks on the different news sites due to differences in HTML structure. We also encountered articles which our library Newsplease (Hamborg et al., 2017) could not parse. We tried not to have any selective biases, for which articles we wanted to analyze and this was done through the randomization process explained in the Methodology section.

Another limitation by using news sites is also statistical power (Appendix 7.2b). The news sites differed in layout and how much they wrote per article.

Limitations by analysis models (SM)

Although ABSA is a great way of integrating context into sentiment analysis, it still faces some challenges. One of these challenges is that the tied up word still can be interpreted in different ways such as the aspect "difficult" which is given a general sentiment score by the bag of words approach. In the context of the conflict a sentence like "The Russians are having a difficult time" would have a negative compound score of -0.36, however in the context of Ukrainian forces, this would most likely be a positive sentence for them resulting in a lot of both false positive- and false negative sentiment scores. To address this limitation, we could have used other tools such as AllenNLP's (Gardner et al., 2018, p. 3) textual entailment model to compare sentences and predict whether the facts in one sentence imply the facts in the other.

Other limitations by using ABSA include that our scraped data might have been a quote by someone else, which do not accurately reflect the sentiment intended by the original author. ABSA is also not able to distinguish irony from intention.

By using VADER (Hutto & Gilbert, 2014) we also encountered some limitations. Since VADER uses a lexicon it has some words, which does not have a sentiment score and provides a neutral sentiment score instead. The mean compound scores received for the research were influenced a lot by the neutral statements either because they did not have a sentiment score or because the sentiments were neutral resulting in our mean compounds fluctuating a lot around the number zero.
By using the non-parametric Wilcoxon Rank Sum Test our data are not required to be normally distributed (Ford, 2017) but because of this, it might have made the results less precise. Also it is important to state that our results of the Wilcoxon statistic "W" values are not directly comparable to each other, as this value depends a lot on the sample size of the data, and since we have a lot of compound values equal to zero then this might in some cases give us a very big W statistic. The samples which we compared to each other are also only approximately the same shape, so this might also have provided a more uncertain result. By using the Wilcoxon rank sum test on multiple different aspects, we also might have encountered type I and type II errors.

For TF-IDF some of the limitations we encountered was that preprocessing of data required a lot of steps. Hereby, some relevant information might have been lost along the way. If the data preprocessing did not involve translating the corpus for Telegram, a more accurate TF-IDF could have been made. The issue could also have been dealt with by using better translation tools. Optionally the TF-IDF method could have been used on the main text corpus for both Telegram and news articles, and would have resulted in more accurate unique words, but this also would have resulted in a lot more data preprocessing due to cluttered datasets. TF-IDF is a method which severely penalizes any word which appears in all four datasets and neglects the word completely, which could also be a limitation.

4.5 Avenues for further studies or analyses (SM)

One of the avenues one could take for further studies on this subject would involve including more Telegram channels as well as a larger amount of news sources. One of the key limitations, which has been described in limitations by using news sites and Telegram, was the fact that it had a large dataset from few sources where if it had broadened up for more various sources with fewer articles and messages, the output would have reflected the general discourses and narratives more adequately.

For future studies on this subject, we would recommend further correlational testing between the Telegram and news. This might be done through implementing tools like machine learning by analyzing sentiments of aspects over different time spans to see if something stated in the news is stated the same way in the Telegram channels and vice versa. Applying techniques as textual entailment (Gardner et al., 2018) as mentioned earlier could also provide insights to how false information and a false picture might be spread as stated by Khaldarova & Pantti (2016). One could also look further into how Telegram is being used in other countries compared with the news and see if the effects are the same as we found.

Further correlational testing could also be done by comparing the public Russian opinions as provided by Levada Center (2022) and Ukrainian public opinions provided by Statista (2022) to quantitatively see if there is a correlation between the public sentiment and the media towards the war. More variables could also be taken into consideration such as lost materials on the battlefield, casualties, missile strikes, downtime of the energy grid etc.

5. Conclusion (SM)

Our analysis revealed some differences and similarities in use of language by different news sources in the Russo-Ukrainian war. We found this by looking into unique aspects used by the respective news sources and also by investigating general narratives used by these. Further when comparing sentiments of the description of certain aspects, we found both some differences and similarities between Russian and Ukrainian news sources. It is discussed how these narratives used by news sources can have an impact on how the population perceives information. Further studies could investigate how news sources might impact the narratives of the Russian and Ukrainian population as well as applying other techniques which could reveal potential spread of false information.

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7. Appendixes

7.1 Equations

7.1a TF-IDF equation

$$Term\ Frequency = \frac{number\ of\ occurrences\ of\ word\ in\ document}{number\ of\ words\ in\ the\ document}$$

$$Inverse\ Term\ Frequency = ln(\frac{number\ of\ documents}{number\ of\ documents\ with\ the\ word})$$

$$TF\ IDF = (Term\ Frequency) \cdot (Inverse\ Term\ Frequency)$$

Equation 1: Mathematical explanation of TF-IDF

7.2 Tables

7.2a Sum of aspects collected by each Telegram channel

Russian Telegram channel id's	n	Ukrainian Telegram channel id's	n
1263569229	10953	1699546626	11365
1429590454	9320	1758753986	10492
1372147953	8734	1156935944	6653
1141171940	8680	1161283843	6478
1060797702	7409	1321000286	4866
1647639783	7299	1296224042	4477
1171552896	4978	1234806023	3576
1793081466	3145	1234886121	3397
1439075721	2826	1651362648	1958
1428419119	1708	1467022133	1696
1000150092	997	1126485686	1636
1438869004	92	1142332865	1457
1661226792	25	1700748648	1426
1719098803	2	1595772204	1283
		1589278878	1214
		1332245481	802
		1663208030	643
		1686012322	506
		1721372338	369
		1175848329	340
		1519719682	69

Number of aspects collected by each Telegram channel

7.2b Sum of aspects collected by each news source

source_domain	n	source_domain	n
kyivindepend-ent.com	10828	sputniknews.com	21139
tsn.ua	13428	tass.com	13611
www.kyivpost.com	26905	www.rt.com	1816

Number of aspects collected by each news source

7.2c Tables showing most common compound values

Russian Telegram channels

aspect	mean compound	n
enemy	0.00548	1573
people	0.0321	1540
fighters	0.0721	1183
servicemen	0.00799	1022
forces	0.0485	755
soldiers	0.0349	635
media	-0.0137	603
authorities	-0.0190	600
troops	-0.00275	573
side	-0.00410	568

Showing the 10 most frequent aspects in our dataset made from scraping Russian Telegram channels

Ukrainian Telegram channels

aspect	mean compound	n
forces	0.00495	2368
troops	-0.00505	1787
military	-0.00228	1677
people	0.0136	1326
occupiers	-0.00321	1317
army	0.0134	1050
soldiers	0.0147	1013
enemy	-0.00469	844
head	-0.0102	708
sbu	-0.0168	537

Showing the 10 most frequent aspects in our dataset made from scraping Ukrainian Telegram channels

Russian news sites

aspect	mean_compound	n
countries	0.0243	917
forces	0.00630	670
government	0.00138	584
authorities	0.00431	455
people	0.0242	426
spokesman	0.00981	389
prices	-0.00626	387
diplomat	0.0357	374
troops	-0.000227	359
president	0.0204	356

Showing the 10 most frequent aspects in our dataset made from scraping Russian news sites

Ukrainian news sites

aspect	mean_compound	n
forces	-0.0210	2751
troops	-0.0110	1307
people	0.00714	1172
invaders	-0.0138	1148
war	-0.00227	695
authorities	0.00104	664
officials	-0.00806	553
military	0.00170	519
soldiers	-0.0103	517
army	0.00886	437

Showing the 10 most frequent aspects in our dataset made from scraping Ukrainian news sites

7.2d Wilcoxon rank sum test results from Telegram channels

Wilcoxon rank sum test by Telegram channels

Aspect	p-value	W	n aspect Russia	n aspect Ukraine	Mean compound Russia	Mean compound Ukraine	sd Rus-sia	sd Ukraine
sbu	.10	11888	40	537	-0.073	-0.017	0.237	0.205
soldiers	.005***	304189	635	1013	0.035	0.015	0.209	0.163
war	.048*	69562	311	473	0.034	0.005	0.179	0.167
forces	< .001***	785870	755	2368	0.048	0.005	0.209	0.124
military	.52	377026	446	1677	-0.007	-0.002	0.128	0.096
enemy	.57	658053	1573	844	0.005	-0.005	0.131	0.212
world	.36	24873	164	315	0.039	0.013	0.22	0.233
situation	.004***	68262	461	332	-0.08	-0.12	0.221	0.258
missiles	.76	16421	121	274	-0.004	-0.007	0.121	0.119
attacks	.93	6147	71	174	-0.024	-0.024	0.22	0.163
strikes	.10	2992	76	88	0.044	-0.022	0.243	0.175
position	.043*	1746	61	48	-0.008	0.069	0.225	0.225

Wilcoxon rank sum test results from difference between compounds of an aspect in Russian and Ukrainian Telegram channels.

7.2e Wilcoxon rank sum test results from news articles

Wilcoxon rank sum test by news articles

Aspect	p-value	W	n aspect Russia	n aspect Ukraine	Mean compound Russia	Mean compound Ukraine	sd Russia	sd Ukraine
sbu	NA	42	7	12	0	0	0	0
soldiers	.56	12312	49	517	0.004	-0.01	0.128	0.155
war	.63	27861	82	695	0.003	-0.002	0.187	0.2
forces	< .001***	863981	670	2751	0.006	-0.021	0.102	0.133
military	.52	77587	303	519	0.007	0.002	0.098	0.132
enemy	.008**	6737	30	374	-0.07	0.014	0.166	0.167
world	.77	11705	88	270	0.018	0.005	0.173	0.217
situation	< .001***	45254	265	415	-0.05	-0.126	0.188	0.248
missiles	.65	9765	65	306	0.023	0.008	0.095	0.113
attacks	.33	4582	53	183	0.007	-0.036	0.182	0.178
strikes	.023*	4296	44	223	0.011	-0.023	0.185	0.163
position	.70	1090	57	37	0.033	0.057	0.185	0.182

Wilcoxon rank sum test results from difference between compound of a aspect in Russian and Ukrainian news sites.