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Empirical Studies of Russian–Ukrainian War Related Fake News – Part 2[5]

Abstract

The Russian–Ukrainian war, which broke out on 24 February 2022, resulted in several paradigm shifts in cyberwarfare. One aspect of these changes is psychological operations. Russia and Ukraine have conducted extensive psychological operations campaigns to fulfil their war aims, which have since been intense along modified objectives. This series of studies examines the impact of war-related fake news through various empirical research. In the first part of the paper, the authors read the emergence of psychological operations and related terms in the international academic literature using network analysis methodology. In the second part of the paper, the authors use sentiment and network analysis to investigate the spread of different fake news. In the third study, the authors measure the attitudes toward the perception of the Hungarian Defence Forces from the perspective of the war in the neighbouring country.

Keywords: Russian–Ukrainian war, PSYOPS, cyberwarfare, network analysis, sentiment analysis

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Introduction

The technological revolution of the 21st century, combined with the rapid development of info-communication tools (ICT) and the growing number of users on different online platforms, has identified new types of security risks in cyberspace. Consequently, the significantly increasing information and, more specifically, psychological operations, even as part of hybrid warfare, can be an excellent breeding ground for the prevalence of social media fears due to the lack of appropriate regulations on the part of service providers and the lack of a proper cybersecurity attitude on the part of individuals, among others. These platforms are also crucial as the various social media platforms are now the primary information and communication platforms, considered almost exclusive from Generation Y upwards.

Meanwhile, on 24 February 2022, Russia's attack on Ukraine broke out a war between two sovereign nations of an intensity not seen in Europe for decades, which, in the specificity of our modern information society, has thematised a significant part of online platforms from the very beginning to an unprecedented extent. In this context, it is in the primary interest of the opposing parties to convince their populations, from a domestic political point of view, the populations of the opposing country, and the world public opinion, from a foreign policy point of view, of their preferred interpretation of events.

Defending against such actions is a solemn task for a state, or in some cases a community within a state, because they exploit the basic human-based vulnerabilities, identifiable in the cognitive dimension, along which a community, or, more broadly, even the whole society, can be manipulated. The attackers, or more precisely the exploiters of these vulnerabilities, can be identified as individuals, cybercriminal groups, hacktivists, cyberterrorists, various intelligence services, or even state actors, or indirectly, for example, through the formation of opinion clusters, a wide range of service providers, commercial and economic groups, as well as non-state actors. As regards the analysis of the motives of the actors, it should be stressed that they are not limited to financial gain or to influencing decision-makers to deceive society, since the attackers may have as their objective the destruction of the fundamental values of democracy of which there have been several examples in recent years. Along these lines, it is essential to note that the various forms of influence are a challenge in countries that are not – fully – democratic and where attempts are made to make the democratic opposition impossible to influence, including through various information operations.

There are two main complementary objectives of our research:

- We aim to use sentiment analysis to measure the international public and Hungarian (more precisely, English and Hungarian) public opinion on the Russian–Ukrainian war, the posts and reaches of keywords and phrases related to Ukraine and refugees, and the emotional associations that society has with them, using so-called sentiment analysis. By examining the results of this empirical research, conclusions can be drawn regarding domestic and international perceptions, attitudes, and trends toward Ukraine and refugees.

- Our aim is also to analyse the perception of Russia and Ukraine in the context of the Russian–Ukrainian conflict from a network theoretical approach, as well as the support, the emergence of specific positions and patterns in the online space related to the countries and the Russian–Ukrainian war.

In the process of elaborating the research topic, we formulated the following hypotheses:

- H1: The number and reach of posts containing "Ukrainian" and "refugee" have followed the same trend in Hungarian and English.
- H2: Regarding the perception of refugees in Ukraine, both Hungarian users of online platforms and the global public tend to have a more positive emotional attitude towards online posts about Ukrainians and refugees.
- H3: From a network science perspective, isolated clusters are more likely to form on online social media platforms when promoting the Russian narrative versus the Ukrainian one concerning the Russian–Ukrainian war.
- H4: Network analysis can be effectively used to identify disinformation operations.

It should be noted that our initial study's extensive exploration of the scientific literature has yet to be replicated.

Methods

Following our research objectives, our research methodology can be structured along two complementary lines: sentiment analysis and network analysis.

Sentiment analysis

SentiOne is a platform for monitoring and analysing mentions and articles published on public Internet domains. In general, SentiOne's sources include websites and social media platforms. All monitored contents are indexed in one shared database, and results are available instantly after configuring a project. SentiOne's database includes over 20 billion mentions and expands second by second. Projects can be configured in over 70 languages. SentiOne uses its own unique language detection algorithms that combine linguistic features as well as additional metadata, which achieves 99.93% precision.

The system is deployed on over 200 dedicated servers and runs on an open-source stack. Each day, new domains are added to the system automatically and manually using web search APIs. Domains are searched using keywords in the topic configuration defined by SentiOne users.

SentiOne tries to gather as much data as possible for further analysis when crawling websites. It monitors domains with user-generated content like blogs, forums, news, and review sites. SentiOne uses a proprietary algorithm to extract data from unstructured HTML content. The data extraction process is streamlined by creating manual XPath profiles for domains on which automatic algorithms fail or domains that use dynamic content.

Social media aspect within the sentiment analysis

SentiOne gathers data from various social media sites through their official APIs.

Regarding Facebook, public fan pages can be monitored, yet SentiOne cannot monitor private users even if their published content is marked as public. Most popular fan pages are discovered and added to the system automatically. New pages are searched using keywords defined in Topics. Twitter provides a public API for monitoring and indexing tweets. SentiOne searches for tweets using keywords from Projects and using streaming API that allows us, in the majority of cases, to gather new tweets instantly. From Instagram, SentiOne uses public API that allows to search for hashtags and users using keywords defined in Project configurations. Due to Instagram's new API rules (valid from 10 December 2018), there is a restriction that a single authorised account system can crawl at most 30 unique hashtags during a week timeframe. SentiOne is getting Instagram Stories from authorised accounts as well.

SentiOne uses public YouTube API to search for videos and comments. Due to API restrictions, mentions from YouTube can be stored for 30 days and cannot be visualised in the Analysis section.

SentiOne's sentiment analysis is based on research by John R. Crawford and Julie D. Henry. They analysed the Positive and Negative Affect Schedule (PANAS). Based on their study, SentiOne's developers created algorithms that help determine the author's emotional attitude to the discussed topic. SentiOne uses proprietary artificial intelligence algorithms to classify the overall sentiment of posts.

Since gender is relevant in this research, the software uses a knowledge-based approach in gender classification algorithms. The system automatically detects the author's gender based on the dictionary of over 35,000 names and analyses linguistic features that determine the author's gender.

Based on the above and the research objectives, we analysed the different emotional content and interactions on the Internet related to Ukraine and refugees according to the following criteria:

- The keywords are "Ukrainian/Ukrainian" and "refugee/refugee".

We intended to avoid pejorative terms and conceptual approaches when defining the keywords.

The analysis was conducted in English (as a world language) and Hungarian. (Even in Hungarian, the algorithm can determine the emotional attitudes towards content and access with ~87% accuracy.)[6]

The time interval defined and tested:

- 24 February – 20 December 2022. (Ten months after the outbreak of war to assess and study trends.)

[6] Bányász et al. 2022.

The amount of data collected:

- Content: 2,309,990 records
- Reach: 12,695,181,085 reactions

All of the analysed data are also available from open sources.

The other methodology of our research was the network analysis. This methodology allows us to investigate the spreading patterns of content on different platforms. For the network analysis, we used the software Netlytic. This text and social network analysis software can automatically summarise and visualise public online conversations on social networking sites, including Twitter.[7] The network analysis language was English (as the world language).

Results

As already mentioned above, the study aimed to analyse the sentiment related to the shared content and accesses, identify the contextual emotions that can be extracted from the context, and conclude the different language areas (more specifically, for the global/international context, English, and the Hungarian language in the domestic context). The languages studied were English (as a global language) and Hungarian.

The investigation focused on content and its accessions containing "Ukrainian" and "refugee" terms. Thus, we analysed these terms in both English and Hungarian about the following:

- the gender distribution of content sharers
- the chronological distribution of content
- the chronological distribution of reaches
- time distribution of positive and negative emotional content
- the aggregation of positive, negative, or neutral perceptions of the content
- most relevant platforms
- positive, negative, or neutral perception of content related to the most relevant platforms
- most relevant authors
- additional keywords appearing

Findings from the sentiment analysis

Figure 1 and Figure 3 illustrate the combination of the terms "Ukrainian" and "refugee" in English and Hungarian concerning the gender distribution:

[7] Bányász et al. 2023.

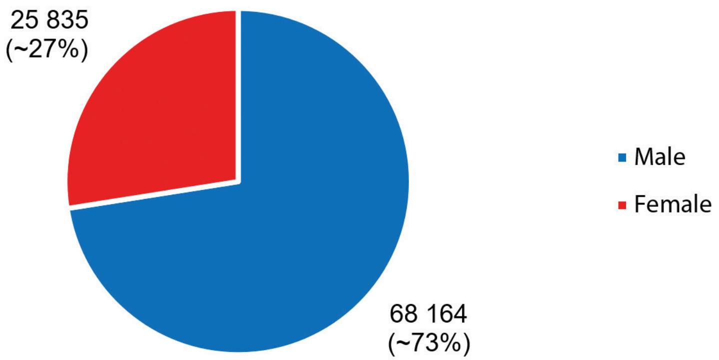

Figure 1: Gender distribution (per person) of Hungarian-language content (male indicated as blue, female indicated as red)
Source: compiled by the authors based on https://sentione.com

The pie chart presents the detailed distribution of gender references within the content related to "Ukrainian" and "refugee" in Hungarian. It reveals a pronounced disparity, with a significantly higher number of references to males, totalling 68,164, in contrast to the 25,835 mentions of females.

This discrepancy suggests that the conversation in this context tends to be more centred around or associated with male individuals.

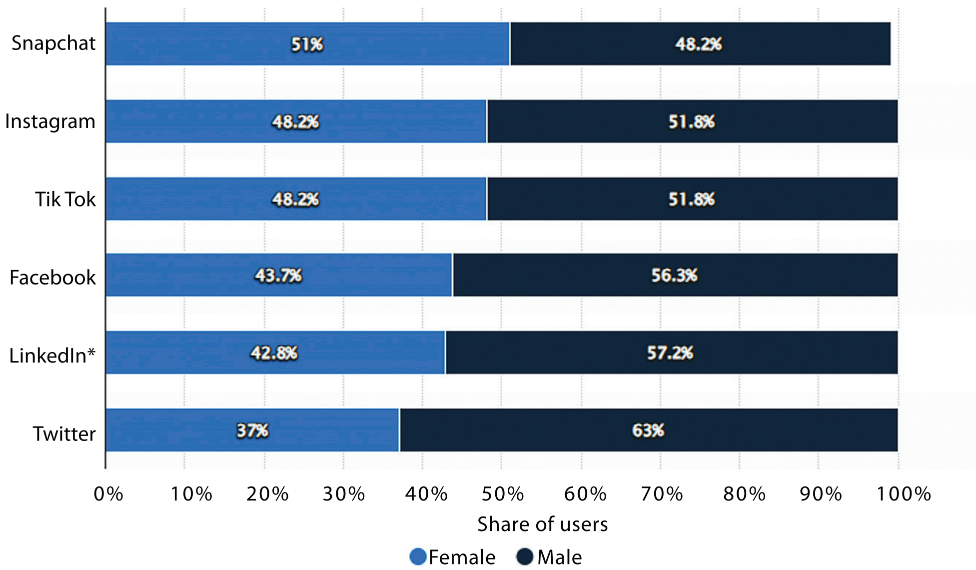

Figure 2: Gender distribution of social media platforms
Source: www.statista.com/statistics/274828/gender-distribution-of-active-social-media-users-world-wide-by-platform

Figure 2 shows the gender-oriented proclivities within social media platforms, demonstrating a preference towards a male-dominant share of users. This inclination parallels the observations made in Figure 1, where there is a notable male gender representation. Such a disparity is not merely indicative of the gender biases inherent within social media usage but also serves to contextualise the pronounced dominance observed in Figure 1.

The substantial male dominance, particularly in the context of the analysed keywords, suggests a broader trend of male-oriented engagement and representation. This trend reflects the underlying dynamics of social media interactions and possibly the societal narratives that drive the dissemination and engagement with content related to the specified keywords.

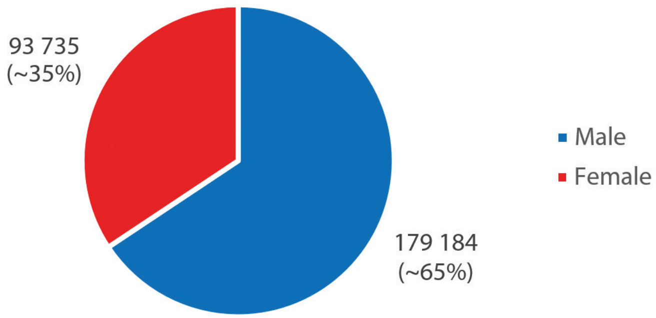

Figure 3: Gender distribution (per person) of English-language content
Source: compiled by the authors based on https://sentione.com

Shifting the focus to the Hungarian part, the analysis presented in Figure 3 reveals that the gender distribution within the Hungarian context for the specified keywords closely aligns with the international trend. This observation suggests a global consistency in gender representation across digital platforms, highlighting a pervasive male dominance. The cross-cultural similarity underlines the universal nature of gender biases in online content, suggesting that these trends reflect broader, global discourse patterns rather than isolated phenomena.

Figure 4 and Figure 5 represent the terms “Ukrainian” and “refugee” together in English and Hungarian concerning the chronological distribution of the content. Observing both data, we can clearly state that there was an initial conversation spike immediately after the war. We strongly believe that the quick drop in attention to the “refugee” keyword happened because the refugee crisis, while initially a hot topic, was resolved relatively quickly. Once the situation was addressed, public and media interest promptly waned, leading to a noticeable decrease in discussions about this topic. After the initial burst of attention, conversations about the refugee crisis occurred every day by June. This pattern shows that public focus can be intense but short-lived, especially when issues are resolved swiftly. It highlights how quickly topics can move in and out of the spotlight on digital media platforms. After the average level, we observed that the keywords remain on topic. Additionally, the topic has shifted from the actual ongoing crisis to a broader discussion.

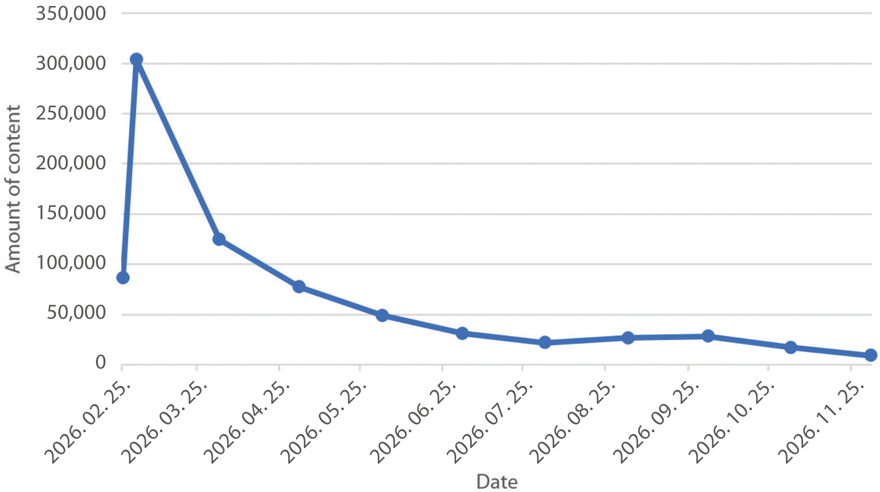

Figure 4: Chronological distribution of the number of Hungarian-language content (pieces)
Source: compiled by the authors based on https://sentione.com

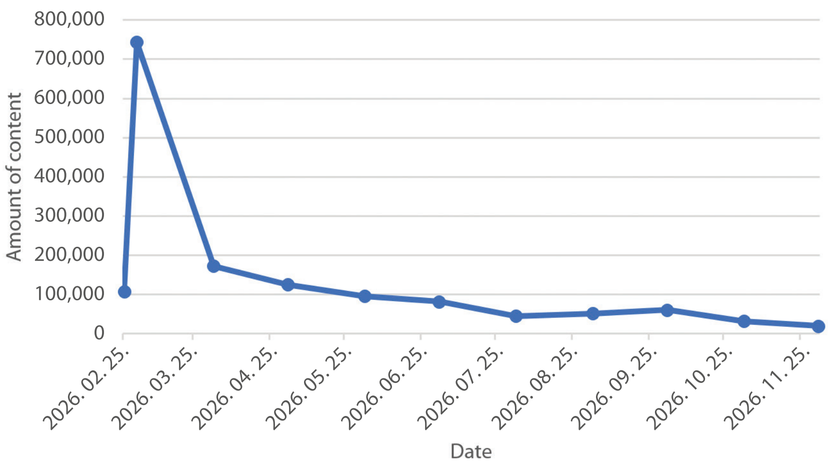

Figure 5: Chronological distribution of the number of English-language content (pieces)
Source: compiled by the authors based on https://sentione.com

In Figures 6 and 7, the terms "Ukrainian" and "refugee" are illustrated together in English and Hungarian concerning the distribution of accesses over time. We strongly emphasise that there's a significant difference between content distribution and content reach. The content reach may overlap with users. One user might look at the same topic from multiple sources; this increases the reach but might not increase the reach of the content. The same spike and normalisation can be observed in the reaches as well. Comparing the two categories of datasets, we can highlight that the spike in reach was more significant than the spike in content. The conversation greatly exceeded the generated content. This indicates how users focused on discussion, not on content creation.

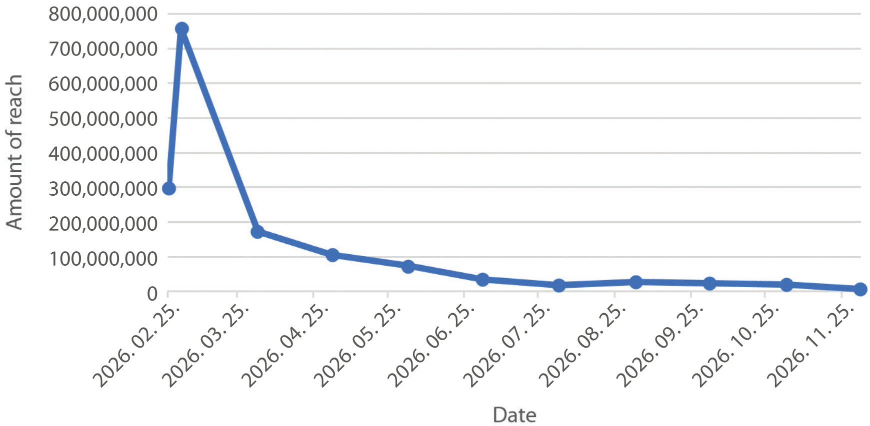

Figure 6: The chronological distribution of the number of reaches in Hungarian (pieces)
Source: compiled by the authors based on https://sentione.com

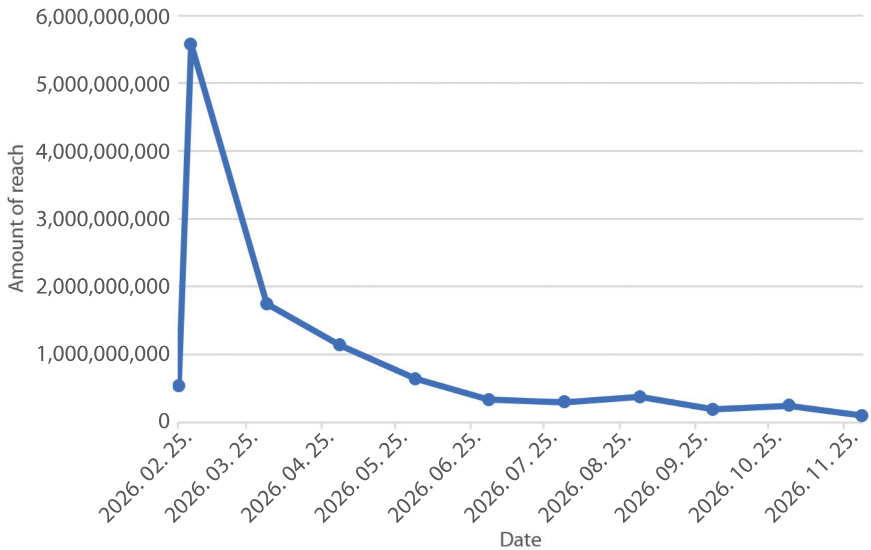

Figure 7: The chronological distribution of the number of reaches in English (pieces)
Source: compiled by the authors based on https://sentione.com

Revisiting our initial hypothesis, which posited that the frequency and dissemination of posts featuring the terms "Ukrainian" and "refugee" showcase parallel trends in both Hungarian and English languages, our observations confirm similar patterns across both linguistic contexts. The slight discrepancy observed is attributed to the fact that Hungarian speakers are comparatively less represented in the global Internet community than English speakers. Consequently, while the volume of such posts is lesser in the Hungarian context, the overarching trend aligns with that observed in English-language posts.

In Figures 8 and 9, the terms "Ukrainian" and "refugee" are presented together in English and Hungarian concerning the distribution of positive or negative perceptions of the content over time. Initially, there were many more negative mentions than positive ones. Over time, positive and negative mentions have decreased, but negative mentions have decreased faster, leading to a closer parity between the two. The rapid decrease of negative mentions displays how users had an initial negative feeling towards the Ukrainian refugees. We suspect as the situation unfolded, users gained a better understanding on the situation, therefore the negativity decreased.

In the English-language content graph, the positive and negative lines come closer together, suggesting a more balanced ratio of positive to negative mentions as time progresses. In contrast, the Hungarian-language content graph shows a consistent gap between the positive and negative mentions, with negative mentions consistently outnumbering positive ones.

Our analysis shows Hungary has a more negative view of the crisis than other places, ignoring neutral opinions found in Figures 10 and 11. This difference suggests that Hungarians are particularly concerned or critical about the situation. We left out neutral feelings to focus on the solid positive or adverse reactions. Reasons for Hungary's negative sentiment could include cultural factors or how the media shows the crisis. Understanding why Hungarians feel this way is essential for addressing their concerns.

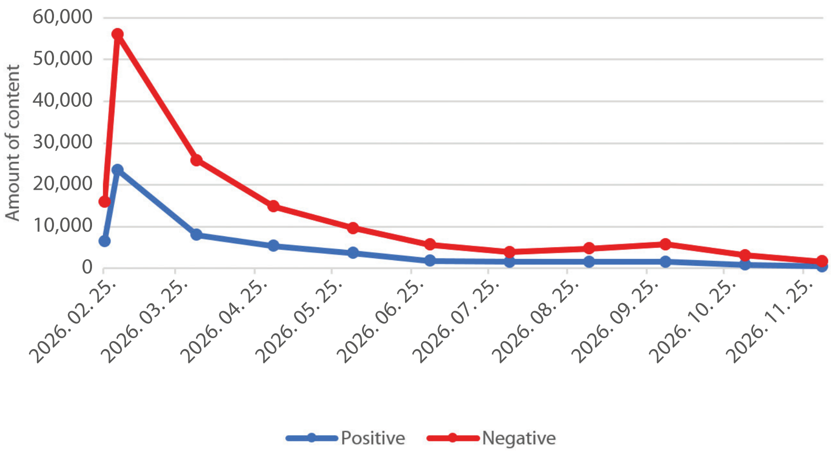

Figure 8: Distribution over time of positive and negative perceptions of Hungarian-language content (pieces)
Source: compiled by the authors based on https://sentione.com

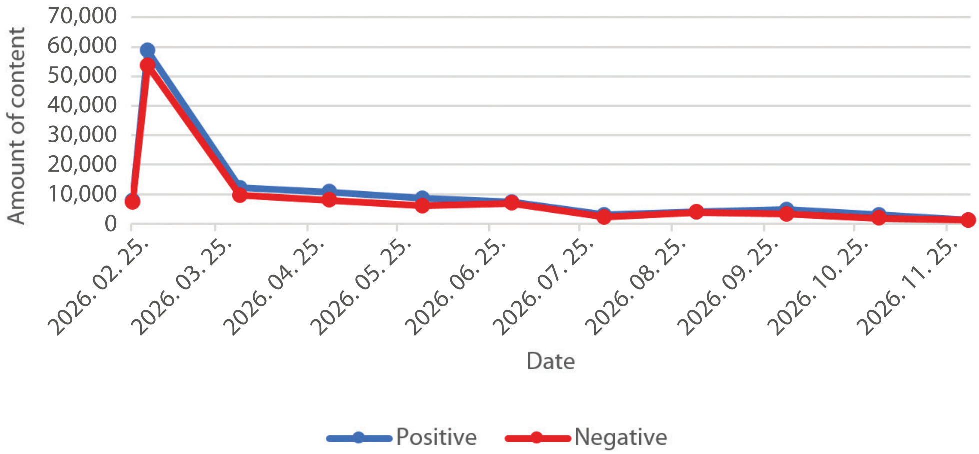

Figure 9: Distribution over time of positive and negative perceptions of English-language content (pieces)
Source: compiled by the authors based on https://sentione.com

In Figures 10 and 11, the terms "Ukrainian" and "refugee" are presented together in English and Hungarian concerning the aggregated positive, neutral, or negative perception of the content.

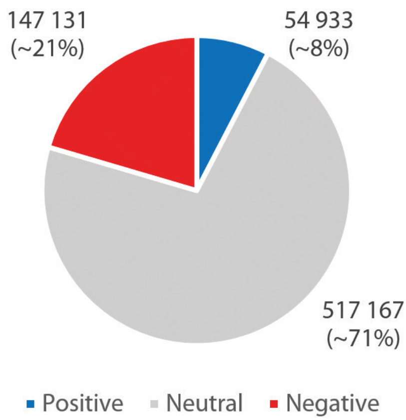

Figure 10: The distribution of positive, negative, and neutral (piece) sentiment in the Hungarian language entries
Source: compiled by the authors based on https://sentione.com

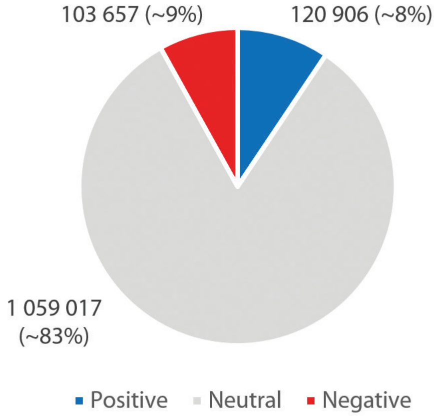

Figure 11: The distribution of positive, negative, and neutral (piece) sentiment in the English language entries
Source: compiled by the authors based on https://sentione.com

Hungarian and English texts show a larger share of neutral expressions in both, but with a noteworthy amount of negative sentiment, especially in English. The Hungarian data has fewer positive mentions than the English data, which has a relatively balanced spread between positive and negative sentiments. Both charts indicate a tilt towards neutral stances, with English texts displaying a more polarised sentiment distribution. Polarisation is a critical issue in our social media-driven world. The Capitol riot of 2021 is frequently characterised as a manifestation of political polarisation and the prevalence of echo chambers, which posed a significant threat to the security of the United States.[8]

Connecting to the second hypothesis – *Regarding the perception of refugees in Ukraine, both Hungarian users of online platforms and the global public tend to have a more positive emotional attitude towards online posts about Ukrainians and refugees* – we can observe a different result than the first hypothesis. We can say that the overall impression appears neutral, mainly involving straightforward reports.

When we delve into the actual emotions of the users, we find that the English language content supports our theory. The second hypothesis stands proven based on the English-language content. On the other hand, the theory does not hold for the content of the Hungarian language. This points to a notable contrast between the two languages, revealing subtle differences in how users react and feel across these linguistic contexts. Such distinctions may stem from cultural variances, the proximity of the conflict, different historical backgrounds (especially Hungary as a former USSR satellite state), or linguistic nuances that influence the expression and interpretation of sentiment online. Further investigation into these aspects could provide deeper insights into the dynamics of language and emotion in digital communication.

8 Barrett et al. 2021.

To further understand the sentiments, we have compiled a dataset encompassing the 25 most prevalently utilised keywords within online content, analysed in both Hungarian and English languages. This dataset is systematically presented in Table 1. Notably, the keywords do not necessarily indicate a sentiment but a discussion. The keywords indicate what "topics" the conversations revolve around.

Table 1: Frequency of additional keywords in the content (number)

Frequency of additional keywords in the content			
Hungarian		English	
Keywords	Frequency of occurrence	Keywords	Frequency of occurrence
ukrajnai	43,803	ukrainian	48,126
ukrán	33,570	refuge	40,332
menekültek	32,011	russian	34,786
háború	28,775	country	31,803
ember	28,693	war	31,019
magyar	28,400	say	29,897
ország	27,101	report	28,931
orosz	25,618	nation	27,969
Magyarország	19,473	Russia	27,419
napping	16,882	help	26,365
év	14,881	Ukraine	24,834
európai	13,532	Putin	24,580
Oroszország	13,225	support	23,119
menekült	12,842	including	21,942
határon	12,109	state	21,669
ukránok	11,954	attack	21,477
részt	11,842	forces	21,215
kormány	11,280	continue	20,497
elnök	10,814	city	20,062
területen	10,172	officials	17,969
támogatást	9,342	border	17,646
kárpátaljai	7,396	civilian	16,279
Putyin	6,718	flee	15,370
Kijev	6,594	invas	14,807
Orbán	6,279	kyiv	13,107

Source: compiled by the authors based on https://sentione.com

Figure 12: Keyword cloud of content keywords
Source: compiled by the authors based on https://sentione.com and Table 1

From the dominant keywords, we have created a keyword cloud to visualise and understand this data better, as shown in both states, which primarily consists of the exact keywords regarding the two keyword sets. Hungarian and English spoken languages follow the same trend: they talk about Ukraine, Russia, Refugees, and political leaders, including their own. Both datasets show that war, country, and nation are universally significant. Figure 12 shows that support dominance is an important difference. The English dataset has a higher priority for support-related words, while in the Hungarian, that place is replaced with the keywords related to Hungary – as a nation. This also indicates a cultural difference between the Hungarian and English speakers. Based on the keyword analysis, Hungarians had an inner focus; they were concerned about how this war would affect Hungary and Hungarians, while English speakers were concerned how the war goes and how will it affect Ukraine and Russia.

Table 2 presents the top 6 online platforms with the highest number of posts in Hungarian and English.

Table 2: Frequency of appearance of entries (number of posts)

Frequency of appearance of posts			
Hungarian		**English**	
Platform	Posts	Platform	Posts
Facebook	510,435	Webpages	914,254
Webpages	259,860	Facebook	365,781
Blogs	1,805	Twitter	225,295
Twitter	1,586	Blogs	13,589
Forums	1,106	Forums	8,074
Instagram	53	Instagram	6,750

Source: compiled by the authors based on https://sentione.com

Upon initial examination, a significant disparity becomes evident in the popularity of various platforms across linguistic divides. Specifically, in the Hungarian context, Facebook and websites emerge as the predominant channels, overshadowing the relevance of alternative social media platforms. Conversely, within the English-speaking realm, Twitter and blogs secure a robust foothold regarding post frequency. This observation underscores the nuanced landscape of digital engagement, where linguistic and cultural factors play pivotal roles in shaping online platform dominance.

Table 3 shows the distribution of the positive, negative, or neutral emotional load of the Hungarian-language posts appearing on the most visited platforms.

Table 3: Distribution of sentiment in Hungarian on online platforms (pieces)

Sentiment distribution in Hungarian on online platforms (pcs)			
Platform	**Positive**	**Negative**	**Neutral**
facebook.com	41,849	103,964	364,622
Avg.hu	7,986	23,591	91,781
kuruc.info	2,075	7,923	26,533
vadhajtasok.hu	1,984	5,977	16,980
pestisracok.hu	227	2,025	5,721
444.hu	224	737	3,139
nemzeti.net	0	0	3,093
propeller.hu	101	852	2,138
mandiner. hu	72	402	2,194
ujszo.com	34	187	1,487

Source: compiled by the authors based on https://sentione.com

Table 4 shows the distribution of the positive, negative, or neutral emotional load of the English-language posts appearing on the most visited platforms.

Table 4: Distribution of sentiment in English on online platforms (pieces)

Sentiment distribution in English on online platforms			
Platform	**Positive**	**Negative**	**Neutral**
dailymail.co.uk	44,229	56,204	532,149
facebook.com	49,551	31,767	284,463
twitter.com	21,953	10,306	193,036
theguardian.com	708	1,293	11,211
yahoo.com	0	0	8,183
instagram.com	1,355	157	5,181
headtopics.com	0	0	5,669
heraldscotland.com	256	521	4,521
lawyersgunsmoneyblog.com	335	438	4,293
wonkette.com	327	391	3,601

Source: compiled by the authors based on https://sentione.com

As illustrated in Figures 10 and 11, the platforms exhibit a parallel sentiment distribution, yet a striking divergence is noted when comparing data across the English and Hungarian language spectrums. Specifically, within the English dataset, only Dailymail and Wonkette displayed a sentiment leaning more towards the negative than the positive. In stark contrast, the Hungarian dataset revealed a consistently more negative sentiment across every platform analysed. This discrepancy highlights significant linguistic and cultural variations in sentiment expression, suggesting a more pessimistic outlook amongst Hungarian language platforms than their English counterparts.

Table 5 shows the 30 authors with the highest number of hits for posts written in Hungarian and containing the famous words "Ukrainian" and "refugee".

Table 5: The most famous authors in Hungarian

The most famous authors in Hungarian						
Platform	**Name**	**Posts**	**Likes**	**Shares**	**Comments**	**Followers**
Facebook	Vujity Tvrtko	39	307,207	58,353	11,989	677,995
Facebook	Telex.hu	176	163,844	8,899	15,704	472,024
Facebook	24.hu	175	78,418	5,053	9,870	944,310
Facebook	HVG	174	71,105	4,094	8,884	627,575
Facebook	KárpátHír	383	67,706	5,879	6,404	53,629

The most famous authors in Hungarian						
Platform	**Name**	**Posts**	**Likes**	**Shares**	**Comments**	**Followers**
Facebook	Szijjártó Péter	9	65,810	3,517	3,838	367,715
Facebook	Migration Aid	82	54,515	17,254	1,370	54,026
Facebook	TV21 Ungvár	439	54,389	8,335	3,005	50,537
Facebook	nlc.hu	83	50,461	3,044	3,922	749,575
Facebook	Karácsony Gergely	13	48,927	3,888	1,470	307,449
Facebook	Elemi.hu	79	42,172	4,866	4,224	46,656
Facebook	Vadhajtások.hu	51	40,626	1,891	7,370	75,881
Facebook	Orosz Hírek	13	37,185	5,161	2,391	93,644
Facebook	Tibi atya	20	33,164	1,811	1,091	1 262,708
Facebook	Blikk	140	32,804	1,449	6,176	752,791
Facebook	Számok – a baloldali álhírek ellenszere	56	32,378	11,571	1,342	86,512
Facebook	Fidesz	7	28,366	3,998	3,606	358,081
Facebook	Márki-Zay Péter	15	27,436	2,033	2,624	171,217
Facebook	PestiSracok.hu	81	27,205	1,819	3,244	116,050
Facebook	Orbán Viktor	2	26,130	1,672	2,348	1 271,374
Facebook	444	52	24,956	1,995	2,958	394,142
Facebook	Egymillióan a magyar sajtószabadságért	31	24,933	2,443	1,587	184,711
Facebook	Tarjányi Péter – író és biztonságpolitikai szakértő	26	24,911	4,867	1,003	231,761
Facebook	hirado.hu	154	24,553	1237	3,006	358,092
Facebook	Juhász Zoli	177	23,244	14,020	1,302	74,104
Facebook	Jakab Péter	3	23,050	3,523	1,242	430,840
Facebook	Mága Zoltán	15	22,438	879	985	1 006,131
Facebook	ORIGO	102	21,395	877	2,378	515,078
Facebook	Hadházy Ákos	5	17,641	5,927	1,602	196,489
Facebook	atv.hu	33	16,953	1,401	3,384	389,841

Source: compiled by the authors based on https://sentione.com

Table 6 shows the 30 authors with the highest number of hits for posts written in English and containing both the keywords "Ukrainian" and "refugee".

Table 6: The most famous authors in English

The most famous authors in English					
Platform	**Name**	**Posts**	**Likes**	**Retweets**	**Followers**
Twitter	Jennifer Aniston (@jenniferaniston)	1	2,196,555	0	41,132,261
Twitter	The Kyiv Independent (@KyivIndependent)	47	366,873	61,657	2,215,066
Twitter	President Biden (@POTUS)	5	320,598	45950	28,489,051
Twitter	Reuters (@Reuters)	93	71,015	16,336	25,673,228
Twitter	The New York Times (@nytimes)	65	51,622	12,166	54,626,053
Twitter	Barack Obama (@BarackObama)	3	42,856	7,187	133,343,165
Twitter	MSNBC (@MSNBC)	13	37,603	6,406	4,711,945
Twitter	CNN (@CNN)	46	33,504	7,704	59,900,894
Twitter	Fox News (@FoxNews)	40	31,239	4,920	23,362,512
Twitter	ABC News (@ABC)	53	13,853	3,987	17,675,107
Twitter	AFP News Agency (@AFP)	54	12,879	4,998	2,426,336
Twitter	BBC News (World) (@BBCWorld)	8	10,698	1,710	37,522,394
Twitter	Sky News (@SkyNews)	68	10,245	2,057	8,274,837
Twitter	The Guardian (@guardian)	110	9,871	2,896	10,823,659
Twitter	The Associated Press (@AP)	10	7,934	2,617	16,081,511
Twitter	Greta Van Susteren (@greta)	48	7,539	697	1,163,273
Twitter	Binance (@binance)	8	4,318	865	10,026,131
Twitter	People (@people)	13	3,696	307	7,770,165
Twitter	ANI (@ANI)	11	2,542	250	7,403,258
Twitter	BBC News (U.K.) (@BBCNews)	7	2,429	625	14,792,028
Twitter	Bloomberg (@business)	36	2,333	729	8,850,280
Twitter	TIME	12	2,140	495	18,968,016
Twitter	Daily Mail Online (@MailOnline)	99	1,955	777	2,803,863
Twitter	Forbes (@Forbes)	25	1,764	477	18,405,854
Twitter	The Wall Street Journal (@WSJ)	13	1,605	427	20,389,886
Twitter	Newsweek (@Newsweek)	50	1,365	585	3,590,468
Twitter	UNICEF (@UNICEF)	12	1,327	431	9,323,334
Twitter	The Economist (@TheEconomist)	27	1,232	379	27,026,546
Twitter	The Washington Post (@washingtonpost)	4	834	242	19,965,825
most	TIME (@TIME)	13	390	117	19,426,733

Source: compiled by the authors based on https://sentione.com

Tables 5 and 6 again witness a discernible divergence in platform preferences between Hungarian and English speakers. Specifically, Facebook exhibits unequivocal dominance among Hungarian users, whereas Twitter holds a similar position of pre-eminence among English-speaking individuals. An interesting pattern emerges from the analysis: English-language content tends to have fewer posts, yet these posts achieve a broader reach or yield.

Conversely, data from Hungarian sources indicate a higher volume of posts. Moreover, the landscape of content authorship varies significantly between the two linguistic groups. In the Hungarian context, individuals, particularly influencers, play a prominent role in the dataset, suggesting a significant personal influence on social media.

On the other hand, the English-language data predominantly reflect the presence of traditional media entities, indicating a different dynamic in content creation and distribution. This contrast underscores the cultural and linguistic nuances of digital communication and highlights the differing strategies and impacts of content across languages.

Conclusions

Figure 5, 6, 7, and 8 show no differences in the fundamental trends (public discourse) between the Hungarian and English language areas, which are proportionally the same. The reason for this, in terms of the expressions studied, is partly the outbreak of the war and the fact that more than 8 million Ukrainians left their country after the outbreak of the armed conflict, and migration within the state was almost as high.[9]

Table 5 and 6 show that contrary to international trends in Hungary, Facebook is still the most basic social media platform with the most authors. At the same time, Twitter is dominant in English language use. In global terms, Facebook is not even indexed among the top 30 most accessed author source platforms in terms of reach. From a security point of view, in global terms, this is good news for Hungary and international trends, as psychological operations and disinformation campaigns aimed at thematising public discourse or promoting one's narrative on a global level are also more frequent on social media platforms that are also more frequent on an international level.

Of course, these campaigns can still reach Hungarian users or be promoted by various actors. This includes misleading and malicious disinformation, or even misinformation, which can be "perpetrated" even by a well-intentioned, ordinary user. Furthermore, from the point of view of Hungary's resilience to psychological operations, it should not be overlooked that attackers may also be aware, with the correct background information, of which sites are considered to be dominant and most visited in Hungary so that this statistic can be seen as a negative one.

[9] See: https://data2.unhcr.org/en/situations/ukraine

Figure 8, 9, 10, and 11, as well as Table 3 and 4, show that contrary to the international opinion in English, the proportion of positive content and hits is significantly lower in Hungary than in other countries. Overall, in the context of the high number of negative results, it can be said that Hungarian-speaking users are dismissive of Ukrainian refugees online. This could be a problem for Hungary in several respects.

- Firstly, Hungarian-speaking users are more exposed to possible – even hostile – influence by going against the general narrative and thus the interests and values represented by our allies (EU, NATO). The reason is that, as human beings, users instinctively seek out and agree with opinions contrary to the so-called "mainstream" perception. Such a situation in the public discourse can provide an excellent platform for a possible offensive psychological operation to achieve its objectives to be able to deliver its "message" in the most effective way to the target group(s) (be it economic, political, military, etc.), as the posts that are intended to be heard can easily hide additive elements aimed at influencing.
- Secondly, in the case of an established, specific Hungarian narrative, the negative perception of society abroad – even by our allies – can negatively impact the collective perception of our country. This perception can be expressed in bilateral economic, trade (professional), political, and even military issues, and changing it can be tricky, even with the effective intervention of a country's leadership.

All this applies to the results of the scientific analysis of user-generated content and hits on online sites. Our research does not include the political leadership of Hungary as a specific aspect of the study; the conclusions are drawn entirely at the social level, based on the information and professional theoretical background available to us.

Table 1 shows inconsistencies, or more accurately predict, between the other keywords that appear and the negative emotional charge described earlier. Among the most frequently appearing keywords, the terms "Transcarpathian" and "(cross-border)" appear as well, which leads us to conclude that Hungarian-speaking users are concerned about the situation, support, and assistance of Hungarians living beyond the border. However, despite this, Hungarian users have a negative attitude towards the issue of refugees concerning the trends detailed above.

This negative trend is further exacerbated by the English keyword "help", which is in 10th place, and "support", which is in 13th place. In contrast, in the case of Hungarian-language content, only support appears among the top 30 terms and only in 26th place.

Network analysis

Regarding the sentiment analysis results, we chose Twitter as the platform for the network analysis, as shown in Table 6, due to the international trend in the global use of this social media platform.

The continuous creation of data and tweets on Twitter means that the networks visualised in this chapter change regularly. At this stage of our study, it should be emphasised that the results refer to the period in consideration (usually one week before the research) so that the visualised networks may take a different form at other times. Moreover, these trends may be influenced by several factors, including external ones, which I will highlight at the points concerned.

The research covers two time intervals:

- from 3 to 10 October 2022
- the period from 16 to 23 April 2023

When visualising networks, the coloured elements represent clusters; each colour represents a different cluster. This is the programming notation, i.e. the set of points that define the network. The colouring better highlights the interconnectedness of a given centralised element.

In network research, graphs are visualised according to their type and number of degrees. From these data, you can see the group of users through whom the information reaches the most people and consequently forms the network's central elements. In addition, network points have been visualised as bridge elements. Here, you can see the users without whom the information would not spread to another network. With the central issues and bridge elements, the AA network would be complete and marginally complete.[10]

We collected data by looking at the occurrence of the following keywords in the periods mentioned above:

- standwithukraine
- standwithrussia
- russiainvadedukraine and #stoprussianagression
- standwithputin and #istandwithputin[11]

Findings

The user account observed on Twitter between 3 and 10 October 2022, spreading with astonishing speed and efficiency, was called "@partisangirl". The trend was brought to the attention of the Hungarian professional community by Ferenc Frész. The account name has since been changed and has been subject to several restrictions. About the extremely short time and the high reach of the network shown in Figure 13, it can be said that it is very likely that the user could have relied on the practical help of so-called "trolls" and "botnets" to promote the user, as such a large-scale spread of a network of this scale by an unknown author cannot be considered organic overall.

[10] Bányász et al. 2023.

[11] Bundtzen et al. 2022.

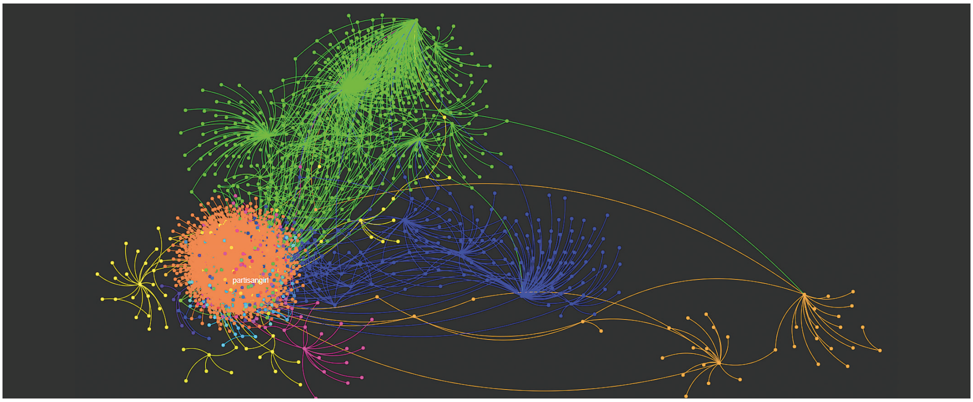

Figure 13: The spread pattern of the Twitter account@partisangirl between 3 and 10 October 2022
Source: compiled by the authors based on https://netlytic.org/

Looking into the visualisation, we can observe how key users are spreading the content further. Additionally, the spread is located very well; there are only a handful of hotspots, and there's no node connection between the spreading users. These observations alone do not indicate a "botnet" or "troll" activity; however, when multiple elements are present, we can state with a high degree of confidence that the spread of the content was assisted.

Figure 14 and 15 illustrate the networks formed by the term #standwithukraine.

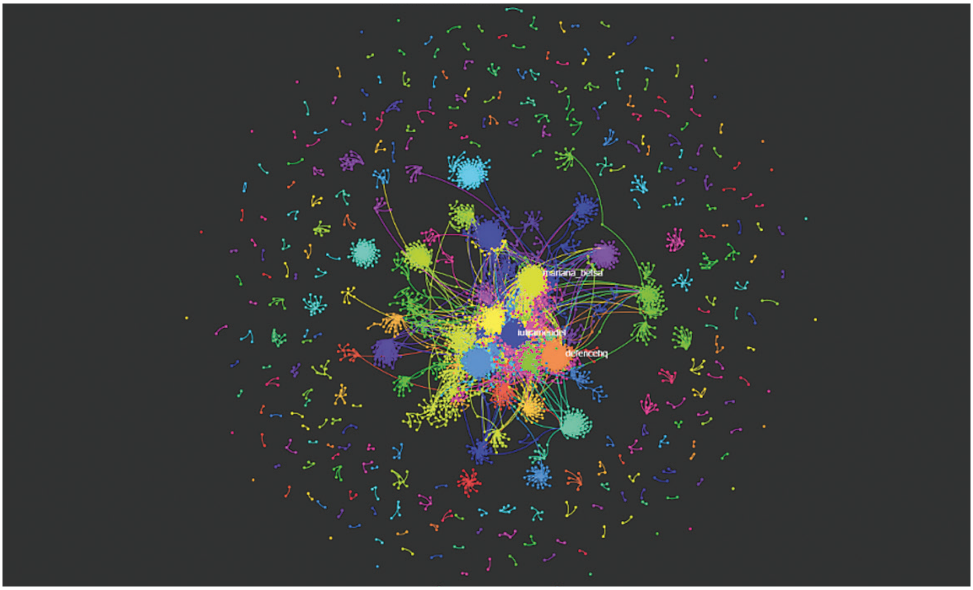

Figure 14: Patterns of networks around #standwithukraine I
Source: compiled by the authors based on https://netlytic.org/

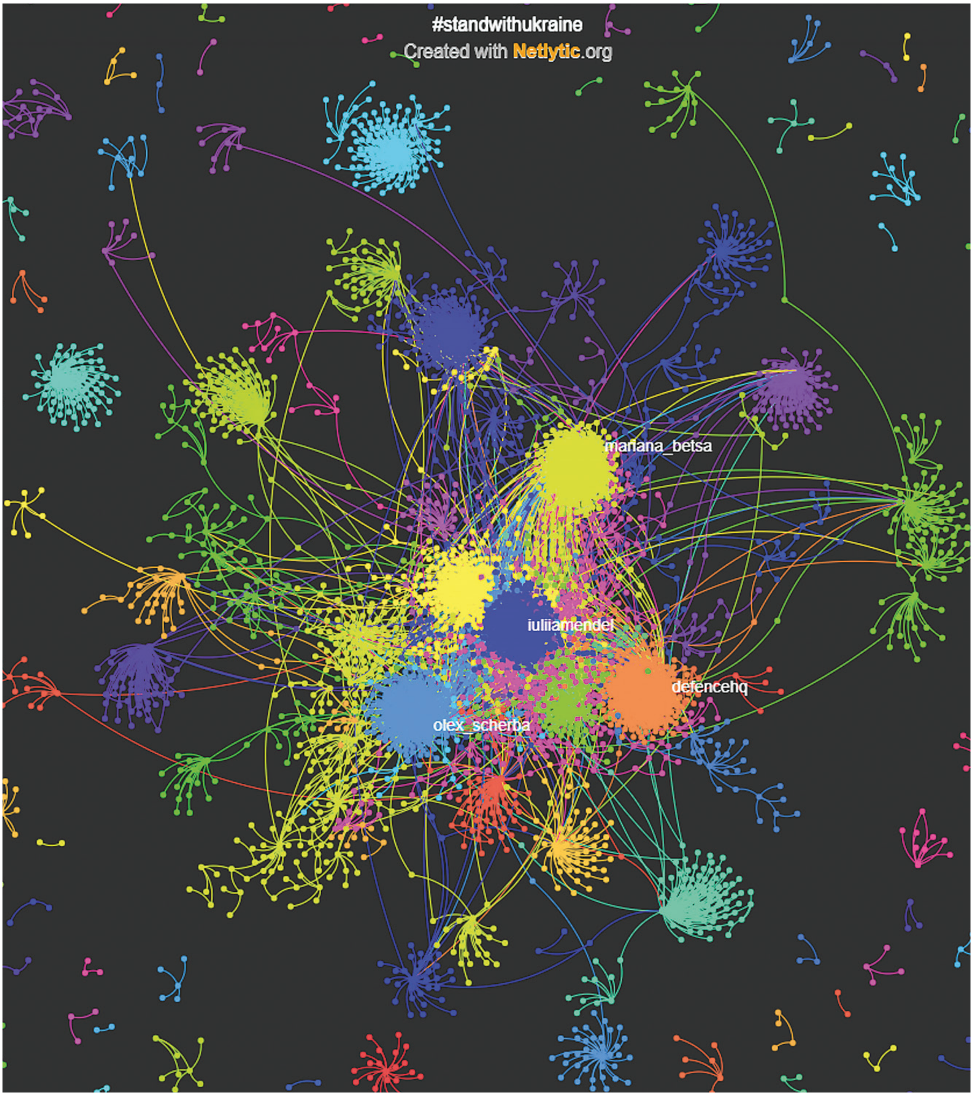

Figure 15: Patterns of networks around #standwithukraine II
Source: compiled by the authors based on https://netlytic.org/

Both these figures show a very different network compared to Figure 13. We can see hotspots similar to those in Figure 13. However, there are significant differences just at the hotspot level. The hotspots are smaller and more localised, and the hotspots are connected. This indicates an actual user activity in the data. This means that the users interact with each other and with each other's content. Meanwhile, the suspected "bot" assisted data showcases a spread from one key user, not a user interaction. More visibly, in Figure 14, however, also present in Figure 15, there are "outsiders". This means some users formed conversations around the exact keywords but have not interacted with the hotspots. This is also possible when humans interact with each other, yet it is missing from Figure 13. Moreover, a difference between the datasets is the connection to the hotspots. The hotspots and the users within these interact with each other.

Figures 16 and 17 show the patterns of the networks formed for the term #standwithrussia.

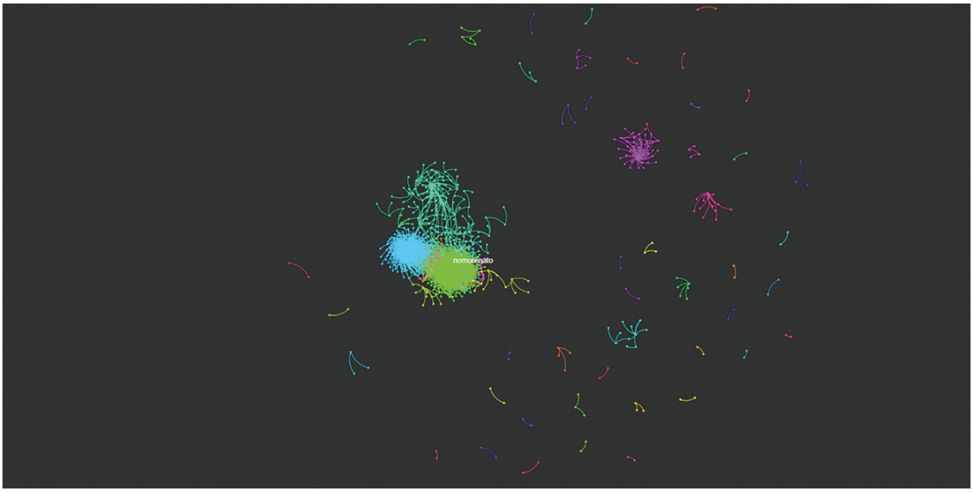

Figure 16: The term #standwithrussia patterns of networks around the phrase I
Source: compiled by the authors based on https://netlytic.org/

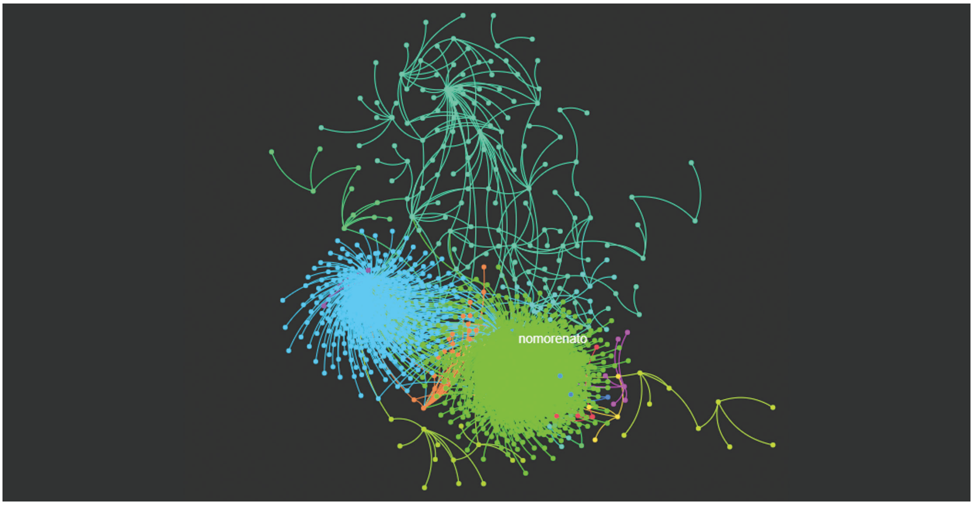

Figure 17: The term #standwithrussia patterns of networks around the phrase II
Source: compiled by the authors based on https://netlytic.org/

The issues we spotted in Figure 13 also appear in Figure 16 and 17. However, there's an exciting twist in Figure 16 with something we call "outsider nodes". These nodes look like they come from real people, but the solid and tight-knit hotspot we see in both images makes us wonder about "botnet" and "troll" involvement. When we get to the last image of this section, it's clear that mainly two users (highlighted in blue and green) are behind the spread of the hashtags. This adds a neat layer to our findings, showing how just a few individuals can significantly influence how things spread online. Connecting to our third hypothesis, *"From a network science perspective, isolated clusters are more likely to form on online social media platforms when promoting the Russian narrative versus the Ukrainian one concerning the Russian-Ukrainian war"* these results indicate a strong incentive towards a proven hypothesis. However, we still have more data to test the theory.

Figure 18 and 19 visualise the patterns of networks formed by the terms #russiainvadedukraine and #stoprussianagression.

Figure 18 and 19 show a natural user-like spread of the content with some hotspots but clear multiple connections between hotspots and nodes. However, this will change once again in the following two datasets. Figure 20 and 21 visualise the patterns of the networks formed by #standwithputin and #istandwithputin.

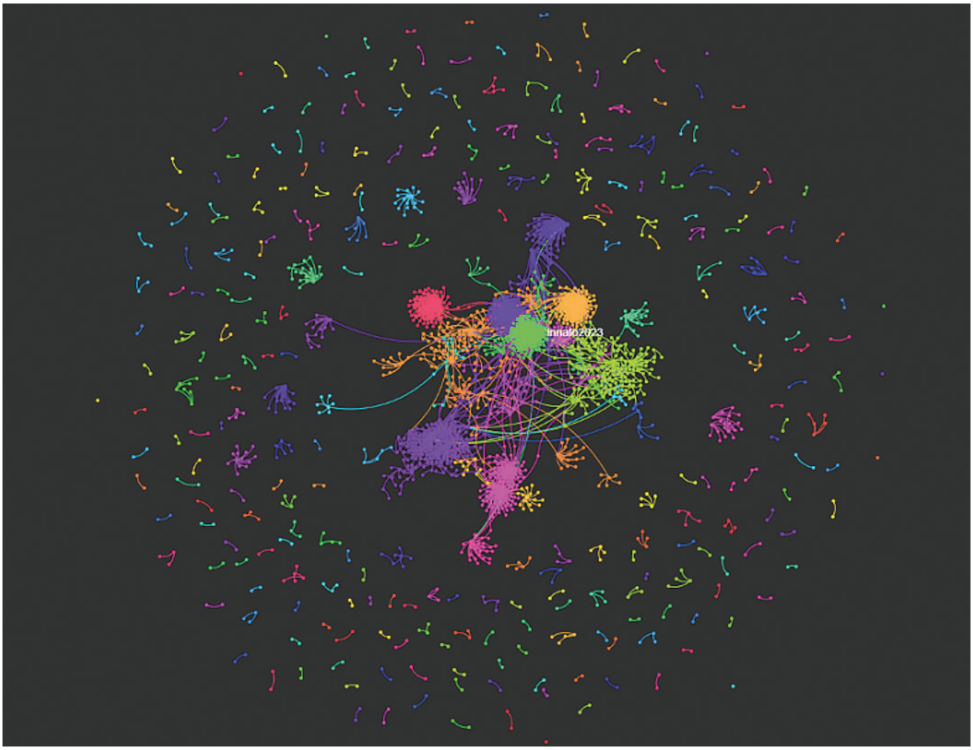

Figure 18: Patterns of networks around #russiainvadedukraine and #stoprussianagression I
Source: compiled by the authors based on https://netlytic.org/

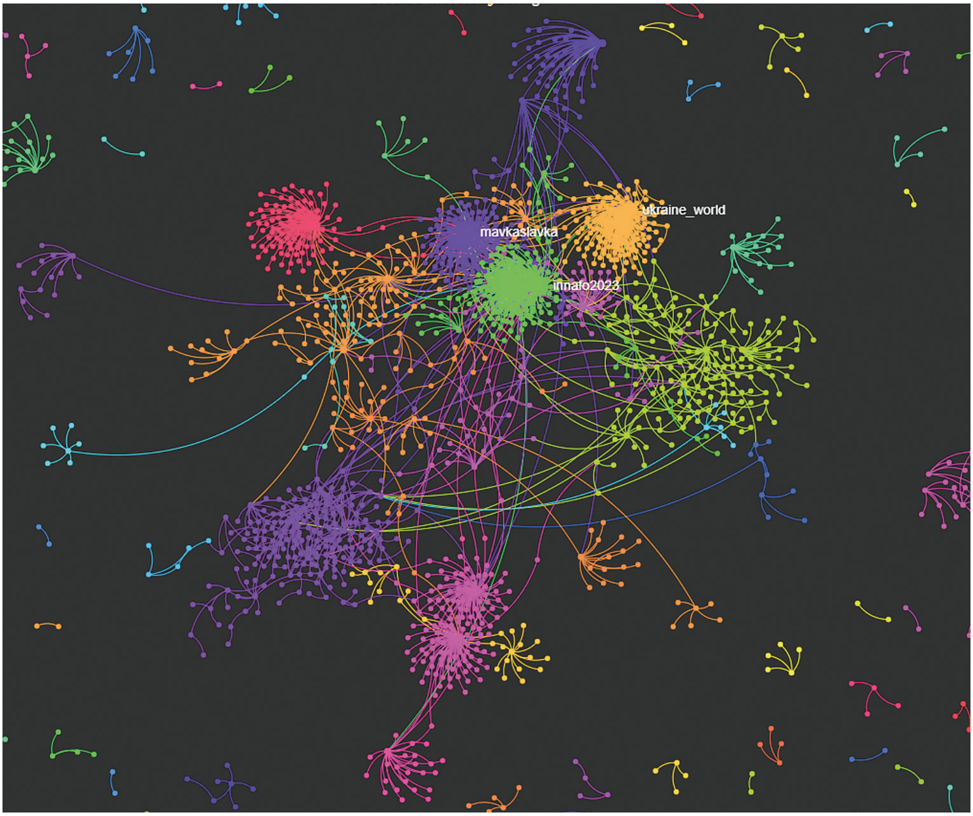

Figure 19: Patterns of networks around #russiainvadedukraine and #stoprussianagression II
Source: compiled by the authors based on https://netlytic.org/

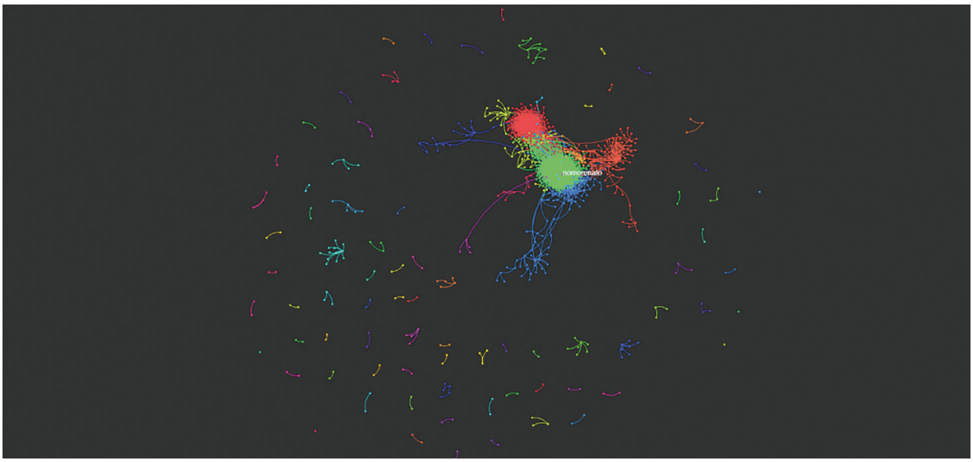

Figure 20: Patterns of networks around #standwithputin and #istandwithputin I
Source: compiled by the authors based on https://netlytic.org/

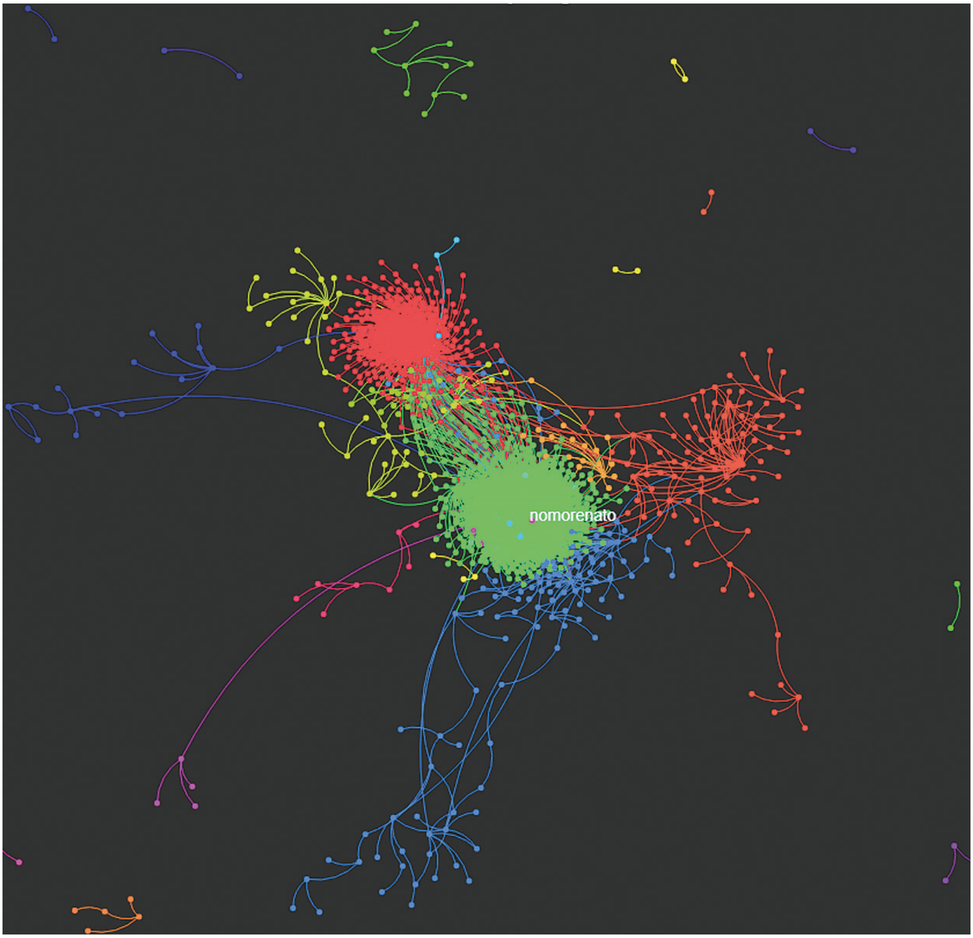

Figure 21: Patterns of networks around #standwithputin and #istandwithputin II
Source: compiled by the authors based on https://netlytic.org/

Drawing from the outcomes of the network analysis, it becomes evident that the third hypothesis has been substantiated. This is closely aligned with the fourth hypothesis, which posits that network analysis effectively identifies disinformation operations. The findings enable us to confidently assert that network analysis holds significant potential for detecting potential operations. This affirmation not only reinforces the utility of network analysis in digital communication research but also underscores its pivotal role in addressing the challenges of disinformation in the modern information landscape. Based on the insights gained from the network analysis, we can confidently affirm that our third hypothesis stands validated. This ties directly to the notion presented in our fourth hypothesis: network analysis is a powerful ally in spotting disinformation campaigns. The evidence gathered allows us to assert with a reasonable degree of certainty that network analysis is helpful and potentially invaluable in uncovering and understanding disinformation efforts. This revelation highlights the significant role that network analysis can play in navigating the complexities of digital misinformation, offering a promising avenue for future research and application in this critical area.

Conclusions

The network research results show an overall decline in the pro-Russian narrative and a rise in support for the Ukrainian side on Twitter, the most dominant social media platform internationally.

The trend of posts containing pro-Ukrainian expressions forming a more interconnected network with more central and bridging elements can be said and seen in Figure 12–19, even though, regarding the spread patterns in Figure 11, the Russian side is investing many resources in promoting its narrative. Regarding expressions supporting the Russian side, there is a higher proportion of isolated clusters with few or no links to other focal points and users.

When examining the results, it can be seen that central nodes with high reach and multiple bridge elements also emerge for the Russian narrative. Still, they cannot connect to additional central elements to the same extent as the pro-Ukrainian entries.

Overall, the international trend on social media platforms is that Ukraine's global support is much higher than Russia's.

One of the benefits of network analysis is the ability to discover propagation bottlenecks that can be monitored, blocked, or triggered. Once identified, appropriate decisions can be made to neutralise the influencing factors, leading to the suspension of the profile or, in more severe cases, the arrest of individuals.[12] In this regard, it is essential to highlight that in the month before our research, at the beginning of March 2023, Twitter suspended around 100 accounts that shared the term #istandwithputin in high proportions.[13]

Discussion

The fight against psychological operations and disinformation campaigns can be identified as one of the outstanding security challenges of our time. The means and purposes of the disseminators of this information can be highly diverse. They may use online or physical means, and their activities may include demoralisation, misinformation, influencing economic, political, or military decisions, imposing or coercing their own will, or appealing to the undecided on a particular issue. In this context, comparing the results of the network research with the results of the sentiment analysis and the description of the operations detailed in the literature, it can

[12] Bányász et al. 2023.
[13] Collins–Korecki 2022.

be said that the position of Hungary concerning the Russian–Ukrainian war and the narrative around it can be considered a matter of concern.

Successful influence operations have unpredictable consequences. As a result, they can have negative implications for Hungary's relations with other countries and society, leading to a loss of trust in the government or the credible media, social tensions, a loss of faith in democratic values, and extremist reactions.

Regarding empirical research on Russia, it is also important to point out that there is a fundamental isolationism towards Ukraine in international public opinion regarding support. However, it is also important to stress that the resources to change this trend are available in the example presented, and it is up to Russian decision-makers to decide when to use them against an unstable community or one that is bucking international trends.

In conclusion, Hungary, with particular emphasis on the decision-making and decision-support segments, must prepare and raise public awareness of the relevance of the dangers and risks involved in psychological operations. With the right resources and international cooperation, good practices can be developed to detect these activities and operations in time and take appropriate countermeasures. Of course, a proper level of public awareness is also essential.

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