“Framing Conflict Discourse”: Audience Co-Commenting Networks and the Framing of Ukraine War Narratives on YouTube

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Contents

Summary of Key Findings

This study examines how YouTube formats influence narratives and audience interactions in the comment section around the Ukraine War. The findings show that Web Documentaries and Infographics encourage broader engagement and overlapping narratives, while Monologues and Web Interviews attract fragmented discussions. YouTube-native channels garner more audience engagement than traditional news channels, creating tighter, more loyal audience clusters despite producing less content. Tools like Gephi and ChatGPT revealed patterns in co-comment networks and comment sentiment, though ChatGPT showed limitations like neutrality bias and oversimplification.

Introduction

Since the outbreak of the Ukraine War, its impact has extended far beyond military destruction and human casualties, permeating various socio-economic spheres and evolving into a global issue. The war has disrupted international economies, partly due to ethical tensions surrounding trade partnerships with Russia (Liadze & Iana, 2022). In the digital realm, particularly on social media, the war has sparked profound discourse as diverse perspectives are shared and debated through user interactions and media content. One notable example of this phenomenon is the activity in YouTube comment sections, where users engage in discussions that often reflect distinct themes. These interactions form interconnected co-commenting networks across related videos, offering a unique lens through which to study audience behavior and the spread of narratives.

Building on this, this research seeks to investigate how different formats of YouTube channels shape narratives about the Ukraine War and to examine the role of audience co-commenting networks in amplifying these narratives. In order to do so, it addresses the following sub-questions:

1. What patterns emerge from the co-commenting networks in terms of audience behavior and discussion topics?
2. How are narratives reinforced through audience engagement and interaction in the comment sections?

By answering these questions, this research aims to provide insights into the dynamics of user engagement shaped by digital content in the context of global conflict events. Furthermore, it leverages Large Language Models (LLMs) for data cleaning, demonstrating their utility as powerful tools in facilitating digital research.

Initial Data Sets

To conduct this research, we used the query "Ukraine War" on YouTube. The data was collected from videos uploaded between April 2024 and December 2024 on a weekly basis. Temporally, the data in the archive does not always align with the collection date, as the earliest video in the dataset dates back to October 2023. Nevertheless, this preliminary dataset generates an extensive list related to the Ukraine War, archiving raw data from up to 157,330 videos. However, the original dataset exhibits a hybrid nature, as it combines both YouTube Shorts and regular YouTube videos. To filter the data, we downloaded the preliminary dataset in a CSV file and opened it in the Wizard Trial data cleaning tool, which excels in handling and processing large CSV files. By applying a filter based on durationSec to restrict the archived videos to those at least three minutes long, we excluded all Shorts from the dataset, reducing it to 78,691 videos. The reason for excluding Shorts from our analysis is that audiences are likely to generate more reflective comments on regular YouTube videos, as these videos are organized to fit a longer format. In contrast, Shorts are relatively limited in their capacity to foster reflection due to their shorter length.

Subsequently, we applied another filter based on view count to rearrange the filtered 78,691 videos in descending order of popularity. By doing so, we identified the most popular videos related to the Ukraine War and manually selected 13 channels based on these videos. We then further filtered the dataset to include only videos produced by these 13 most popular channels, resulting in a condensed dataset of 1,188 videos. As this research focuses on analyzing comments, we observed that three videos in the final dataset had comments disabled, with no comments archived. These three videos were therefore removed, leaving a total of 1,185 videos. From this set, we identified the most viewed video from each channel, resulting in 13 videos in total. Finally, using the YouTube Data Tool (Rieder, 2015), we downloaded comments for each of these 13 videos via the video comments module, with a limit of 1,000 comments per video. The results were output as 13 individual CSV files.

Methodology

Firstly, based on the overall research question and first sub-question, we decided to manually select the most popular YouTube channels which are both news channels and YouTube Native channels, such as individual creators, which led to a selection of 13 channels. We then filtered the dataset as described above to those 13 channels which led to 1185 videos. By using the module video co-commenting network in YouTube Data Tools (Rieder, 2015), we put this CSV file into Gephi, in order to understand the connections of video, based on co-commenters. By doing so, we can understand what patterns surface from the commenters of the channels from the initial data set. By using ForceAtlas 2 in order to see the clusters of the connections between videos based on co-commenters, we further put the nodes on the average degree and adjusted the size of the nodes to indicate the view counts per video. The nodes range in size from 20 to 200. We also color-coded each channel, to distinguish their place in the overall co-comment network.

Furthermore, we selected the most popular video per channel with the most views, that relate to the Ukraine war, which led to a total of 13 videos. Moreover, we categorized them based on formats, according to García-Avilés and de Lara (2018, p. 22). This led to six categories of formats, namely *news formats* (BBC, ABC News, CNN), *Video Blog Infographics or Animation* (Mr Spherical, AiTelly), *Web Interview* (Lex Fridman, Tucker Carlson, VDUD), *Web Documentary or Webdoc* (The Military Show, Spartan, Military Update), *Web Monologue* (Task and purpose) and *Others* (VologdaMapping). Since there is a considerable amount of comments across all videos, in order to analyze them, we used ChatGPT (GPT-4o mini) to categorize the comments per video, to identify the main narratives in the comment section of the selected videos. By uploading a PDF file of the comment section per video, we used the query "Can you identify the main narratives from this comment section?" Since ChatGPT gave different amounts of main narratives, we further asked it to gather the three most common threads of narratives in each video. After doing so, we manually identified three overlapping main narratives among all selected videos per format, as seen in Figure 1.

Findings

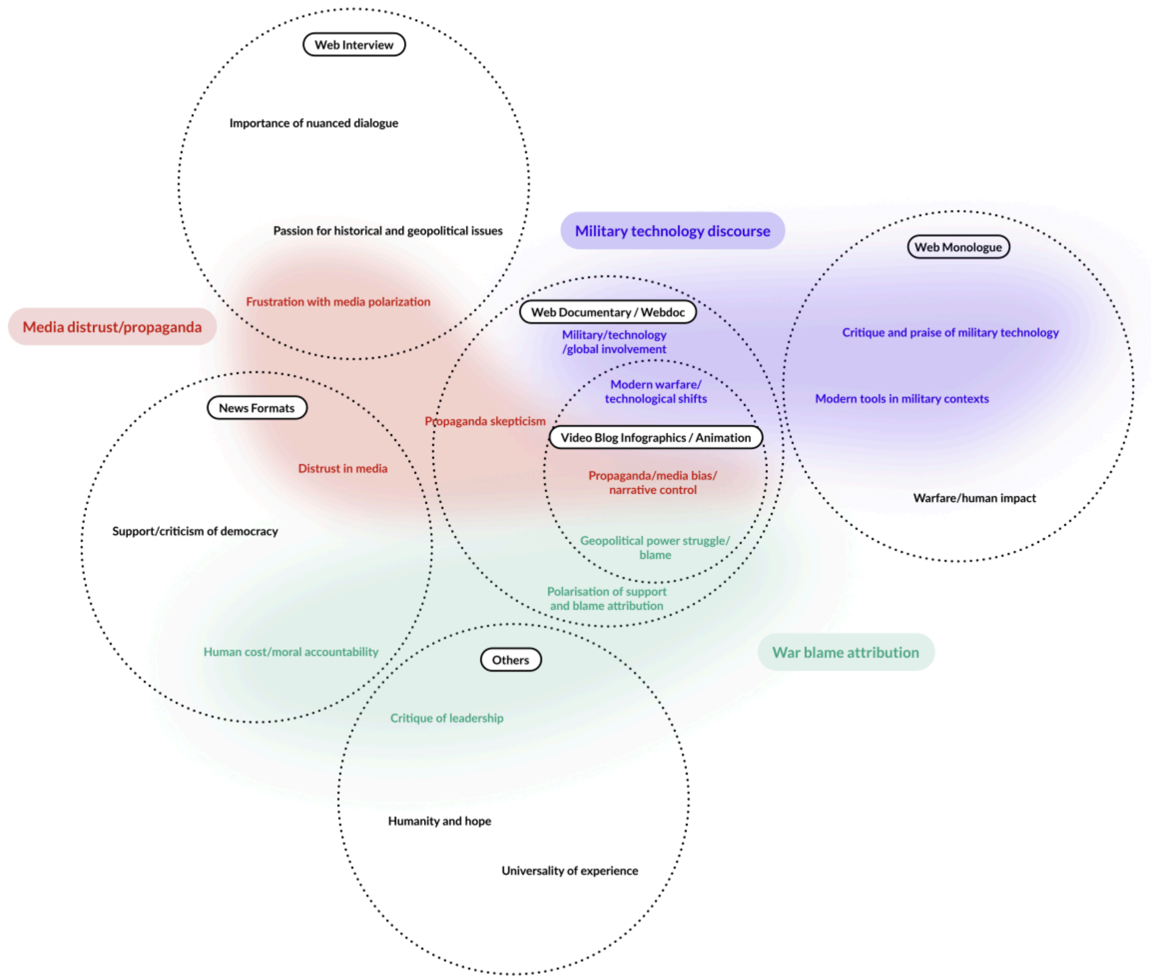

FIGURE 1. Comment sections narrative distribution

Comment sections narrative distribution

Figure 1 shows the main narratives among the selected channels. Firstly, we identified the different formats of the selected videos, to categorize the main narratives that ChatGPT generated for each format. Based on the comment threads that are categorized by ChatGPT, three overlapping narratives can be observed among all formats. For Web Documentary and Video Blog Infographics/Animation, the main narratives are similar, therefore these circles overlap in the figure. Moreover, these formats have three overarching main narratives, while the formats of web interviews, monologues, and others merely overlap with one of the three overarching narratives. Web interviews and others are the least connected formats in the narrative space, in which these contain one overarching narrative. This difference underscores that these longer and more structured formats tend to encourage a wider range of narrative framing, which is because they present multiple perspectives for the audiences.

These main narratives in Figure 1 indicate how commenters, who are mostly either pro, con or neutral position in the Russian-Ukraine war, use similar common themes and narratives in the overall discourse on YouTube. Therefore, these patterns underline the role of formats in shaping how narratives are reinforced and framed in the issue space on YouTube, which aligns with our first sub-question. Since Figure 1 shows how web interviews and other formats are the least connected, this suggests that these channels are more niche in their appeal, in which its main narratives are not as broad. Moreover, the data reveals that monologues and interviews have limited overlap. On the other hand, web documentaries and web infographics overlap all three main narratives, which suggests their accessibility and engagement across different audiences, which can foster an issue space where various viewpoints converge and overlap.

However, it is important to note that these main narratives are generated by ChatGPT, which can lead to implications in categorizing the comments per selected video. The model based on LLM can overlook important nuances or diversity in perspectives among one of the main narratives. Additionally, as stated in the methodology, the differences in the number of narratives identified for each video indicate the challenges of content analysis done by ChatGPT. Moreover, as Rogers and Zhang (2024) state, it is essential to note that LLM labeling has a “bias toward neutrality” (p. 5), further showing the possible lack of nuances in the categorization generated by ChatGPT.

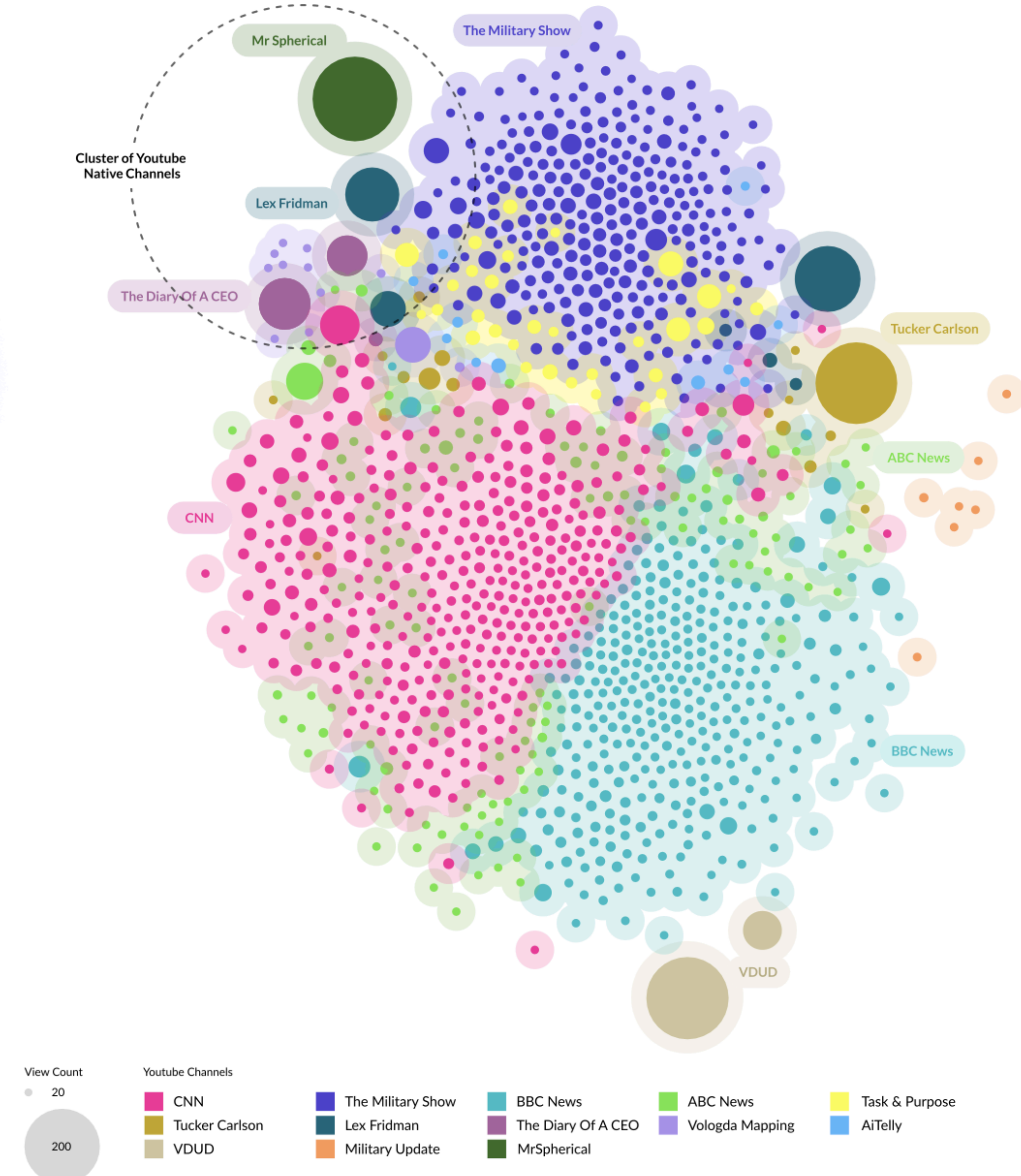

FIGURE 2. Co-comment network using Gephi

Findings of co-comment network analysis

As seen in Figure 2, the co-commenting network showed that all of the comments from the videos from the sample were interconnected, forming a unified yet dispersed web. YouTube-native channels tend to cluster closer together, indicating that their audience networks are more closely connected while remaining slightly distant from the broader network. This clustering can indicate that individual creators with YouTube native channels cultivate more engaged and loyal communities that may interact more with each other in the issue space. On the other hand, ABC News Channel commentators are dispersed throughout the network, unlike the tightly-knit communities observed around CNN and BBC channels. This spreading suggests that ABC News may reach a broader and more fragmented audience, compared to other news channels. The web monologue channel, Task and Purpose, bridges the news channel space and the individual creator space, positioned almost perfectly along the boundaries of these issue spaces, rather than being on the outskirts of the network such as other non-news channels.

Interestingly, YouTube-native channels, run by individual creators, garner more views than traditional news channels, despite news channels dominating the dataset regarding video amount. This may suggest that although news channels produce more content, they appear to garner less engagement from viewers than YouTube Native channels, which provide more personalized and targeted content. Therefore, although news channels would be expected to gather more engagement due to their extensive production capacity and established reputations, they do not dominate the network with regard to viewership. This finding thus demonstrates how there may be a preference for personalized, YouTube native content rather than journalistic formats.

Discussion

For this study, we investigated how YouTube narratives are shaped between different channel themes and how co-commenting networks can amplify the digital discourse between these narratives. How distinct content formats affect the way different narratives are positioned within them aligns with the thematic structures that are identified in media studies. The research done on Chinese state media by Ran and Liu (2024) shows how the thematic organization of the discourse around the Russian-Ukraine war reflects the hierarchical structure of narratives. The dominant themes in state media shape public perception and discourse. Similarly in our study, we found that YouTube formats such as Web Documentaries and Infographic/Animation connected the audiences and allowed different narratives to be discussed, enabling broader audience engagement. On the other hand, Web Interviews and Monologues had less thematic overlap, indicating that the audience is more fragmented in these videos.

Additionally, the clustering of audience interactions in the co-comment network aligns with the findings of the LLM-enabled analyses of online communities. Ziems et al. (2024) highlight that personalized and relatable content fosters tighter community engagement, in contrast, broader and more fragmented audiences are more typical for institutional content like news channels. BBC and CNN have tighter clusters, while ABC News was more spread out in the network, which ultimately showcased varying levels of loyalty and engagement within the news channel community. Nevertheless, compared to YouTube native channels the engagement was noticeably less.

The use of LLMs in our study to analyze comment sentiment provided significant help when it came to analyzing huge amounts of data, but nevertheless, it does raise questions about bias and lack of depth of the final findings. As highlighted by Ziems et al. (2024), LLMs are sufficient for identifying overarching patterns and summarizing content but may oversimplify data. Another notion that is raised is the LLM's tendency for bias towards neutrality, especially when analyzing complex and controversial narratives around the Russian-Ukraine war. While the study offers valuable findings in the overarching war narrative discourse using a significant amount of data, Chat-GTP can present potential oversights when capturing highly nuanced discourse in conflict dynamics. For future research, a hybrid approach of using both LLMs with qualitative methodologies can enhance the depth of the sentiment analysis. Additionally, involving the same number of non-native YouTube channels and native ones with opposing viewpoints could provide more diverse audience engagement data. Looking at the bridges in ideological divide within a network, can offer insights into balanced discussions and propaganda narratives on digital spaces.

Conclusion

This study explored the narrative formations and audience interaction on YouTube within the discourse around the Russian-Ukraine war. By analyzing the sentiment of comment sections and co-commenting networks across varying formats, we saw findings around the interconnectedness and narrative amplification surrounding a divisive and controversial war. Our findings show an alliance with greater digital media trends on the user preference for personalized and relatable content with loyal communities rather than traditional journalistic outlets. However, the amount of content produced by these outlets highly outnumbers those of YouTube native ones in the issue space and should be accounted for.

The use of ChatGPT for comment sentiment analysis allowed us to analyze large datasets which helped us identify the overarching narrative stress across the space. However, we also acknowledge the limitations that this has brought up since there is potential for neutrality bias and oversimplification of the nuanced discourse of the war.

To conclude, this research highlighted the importance of studying platform-specific dynamics and content formats and their role in the spread and shaping of rhetoric in digital spaces. Future studies would benefit from a hybrid approach of using LLMs and qualitative research, perhaps on a smaller dataset, to ensure that the depth of the sentiment is accounted for as well. Additionally, exploring ideological divides within co-commenting networks could provide a pathway for exploring discussions in polarized digital environments. By studying the dynamics and structures of this type of discourse, researchers can gain insights into the role that social media plays in shaping public opinion on controversial geopolitical issues.

References

Ahmed, Shaker, Mostafa M. Hasan, and Md Rajib Kamal. n.d. “Russia–Ukraine Crisis: The Effects on the European Stock Market.” Accessed January 9, 2025. https://doi.org/10.1111/eufm.12386.\

García-Avilés, J. A., & De Lara, A. (2018). An overview of science online video: Designing a Classification of Formats. *Communicating Science and Technology Through Online Video*, 15-27. https://doi.org/10.4324/9781351054584-2.

Liadze, Iana, Corrado Macchiarelli, Paul Mortimer-Lee, and Patricia Sanchez Juanino. n.d. “Economic Costs of the Russia‐Ukraine War.” Accessed January 13, 2025. https://doi.org/10.1111/twec.13336.

Ran, Tongzhou, and Zhangbo Liu. 2024. “‘The Russia-Ukraine War’ or ‘The US-Russia War’? Thematic Analysis of Global Times’ Coverage of the Russia-Ukraine War.” *Media Asia* 51 (1): 3–32. https://doi.org/10.1080/01296612.2023.2246721.

Rieder, Bernhard. (2015, May 5). YouTube Data Tools [Computer software]. https://ytdt.digitalmethods.net/.

Rogers, R., & Zhang, X. (2024). The Russia–Ukraine war in Chinese social media: LLM analysis yields a bias toward neutrality. *Social Media + Society*, *10*(2). https://doi.org/10.1177/20563051241254379.

Topinka, Robert. 2024. "'Conspiracy Theories Should Be Called Spoiler Alerts': Conspiracy, Coronavirus and Affective Community on Russell Brand's YouTube Comment Section." *New Media & Society*, Online First.

Törnberg, P. (2024). Best Practices for Text Annotation with Large Language Models. *arXiv preprint arXiv:2402.05129*.

Ziems, C., Held, W., Shaikh, O., Chen, J., Zhang, Z., & Yang, D. (2024). Can large language models transform computational social science?. *Computational Linguistics*, *50*(1), 237-291.