With just one tap. Network study of tweets dissemination during the war in Ukraine

Abstract. Social desensitization refers to the process by which individuals become less sensitive to the emotional impact of traumatic events, such as those reported in the traditional or new media. This phenomenon has been observed in the past in the context of wars and other violent events (e.g. Syria, Iraq, 9/11). In the paper, we verify the social desensitization hypothesis with a focus on the recent war in Ukraine within the framework of exponential random graph models. We use a Markov chain Monte Carlo simulation to analyze tweets' networks and their properties. Consequently, we investigate users' behavior associated with different aspects of producing and sharing comments on Twitter (e.g. likes, quotes, retweets). We selected and studied tweet networks that emerged during the four different war events that took place between February 2022 and November 2022. We discovered significant differences in the network models' parameters that may be associated with a decrease in empathy. We also identified an increasing homophily of tweet communities and a lower tendency to reciprocate ties within the same language groups. Although these processes are disturbing in terms of their social consequences, solutions already available in scientific contributions could be effectively used to counteract them.

Keywords: war in Ukraine, Twitter, social desensitization, random graph models

1 Intro

During a crisis, understanding the diffusion of information throughout social media provides insights into how quickly people will learn about the incident and react to it. Personal contact or even knowing each other is no longer necessary to pass on the information. It only takes one tap to send the message to the world, resulting in the ultra-fast dissemination of information via complex interconnected virtual networks. However, the prolonged crisis has its consequences on the scope and range of diffusion strategies. Exposure to traumatic events may lead to social desensitization. This was recently observed during the COVID-19 pandemic, where initially we were upset about a few deaths, and after a year, even thousands of expirations did not impress us (see e.g. Stevens et al., 2021 for linguistic study of tweets). Several sources report that exposure to violence in the media reduces its psychological impact (Brockmyer et al., 2013; Krahe et al, 2011), and this drop could be represented by a curvilinear pattern (Fanti et al., 2009). Consequently, the desensitization has been studied and reported in both traditional (Gentile & Bushman, 2013; Mrug et al., 2015) and new media (De Choudhury et al., 2016; Sanchez, 2020). Repeated exposure to graphic news coverage of violent events can lead to decreased empathy towards the victims of those events.

This desensitization to the suffering of others can occur because individuals become habituated to the violent images and their emotional impact decreases over time (Fanti et al. 2009).

Slone and Shoshani (2008) found that Israeli adolescents who were exposed to a high amount of news coverage of violence during the Second Intifada had lower levels of empathy towards Palestinians compared to adolescents who were exposed to less news coverage of violence. Similarly, a study by Cocking et al. (2009) found that individuals who watched a high amount of news coverage of the 9/11 terrorist attacks had lower levels of empathy towards the victims of the attacks. In addition to decreased empathy, individuals who are exposed to a high amount of news coverage of violence may also experience an increased tolerance for violent behavior. A study by Sood and Rogers (2017) found that individuals who were exposed to news of mass shootings were more likely to believe that violence is an effective means of resolving conflicts and were less likely to support gun control measures.

Recent war in Ukraine showed that the battles are being waged in both real and virtual environments. Large-scale disinformation strategies and ongoing desensitization of Western society may be a silent supporter of the Russian invasion of Ukraine and induce compassion fatigue that results in lower willingness to provide help for war victims (e.g. Moeller, 1998; Russo et al. 2020). Moreover, tragic events are often disseminated as memes or jokes that disconnect them from their real context and make them even more abstract (Sanchez, 2020). Viral conspiracy theories spread in the new media gathering millions of users and strike open democracies (Coleman & Sardarizadeh, 2023). Some recent data on Twitter activity of Russian federation prove that there is ongoing organized disinformation campaign: government Twitter accounts, with 7.3 million followers garnering 35.9 million retweets, 29.8 million likes and 4 million replies, tweeted 1157 times between 25 February and 3 March 2022 (OECD, 2022).

The fact is that Twitter is especially strong in news diffusion, because it provides an easy-accessible environment for discussion of multiple users. Comments and news can be easily retweeted to others which result in exponential growth in the number of 'infected' devices (Zhang et al. 2014). Users with a large number of followers create 'bridges' between different social circles (Maireder, 2017) and by implication impact distinct audiences. The better understanding of tweets dissemination can help those who need to respond to events and counteract negative phenomena polarization or social desensitization. The research hypothesis was that together with the duration of the war campaign, people become desensitized, lack empathy and are less likely to produce and disseminate the news that refer to the events in Ukraine due to psychological mechanisms as well as coordinated disinformation strategies. We suspect the phenomenon has its reflection in Tweets' networks and could be quantitatively examined by respective research methods.

We have chosen four significant war incidents that occurred in various time points of war in Ukraine (1. Battle of Chernobyl - 24.02.22; 2. Surrender of Azov steel factory - 16.05.22; 3. Crimean Bridge explosion - 8.10.22; 4. Missiles strike Poland - 15.11.22) and investigate the Tweets networks associated with these events. We assessed selected criteria that may stand for social desensitization and are associated with the probability of tweet formation. In our research approach, we used MCMC algorithm to simulate the Tweets' networks and estimate their coefficients. We then compare these simulated networks to the observed data on various structural properties to reveal which models are sufficient to produce which network properties.

2 Data

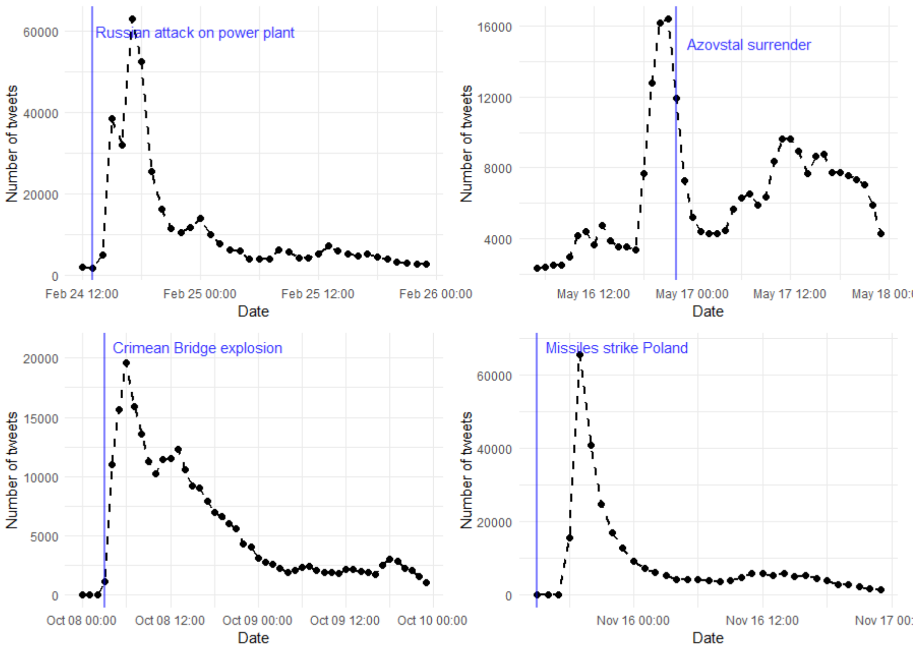
Networks are composed of nodes and edges e.g., who (a node) replies (an edge) to whom (another node), how often (the strength/weight of the edge). In the case of Twitter, users are nodes and Tweets are edges. To produce the networks, we collected Tweets with their metadata. In this procedure, we used Twitter API v. 2.0 with academic license. Table 1 presents the number of collected tweets for specific war events in the Ukraine. In each of the query, we specified the keyword, the initial and the end time of the Tweet to appear. The initial time of events was extracted on a basis of media reports (CNN, BBC) and other reputable internet sources (Wikipedia, Telegram) which are mentioned in the table. The end time was specified to be: initial time + 24h for all the events.

Table 1. Selected war events

no	date	event	twitter query	total no of tweets
1.	24.02.2022	Battle of Chernobyl	query = 'Chernobyl' start_tweets = 2022-02-24 12:00 end_tweets = 2022-02-25 12:00	400249
2.	17.05.2022	Surrender of Azov steel factory	query = 'Azovstal' start_tweets = 2022-05-16 19:00 end_tweets = 2022-05-17 19:00	279385
3.	8.10.2022	Crimean Bridge explosion	query = 'Crimean Bridge' start_tweets = 2022-02-24 06:00 end_tweets = 2022-02-25 06:00	307320
4.	15.11.2022	missiles strike Poland	query = 'missiles Poland' start_tweets = "2022-11-15 15:40", end_tweets = "2022-11-16 15:40"	288599

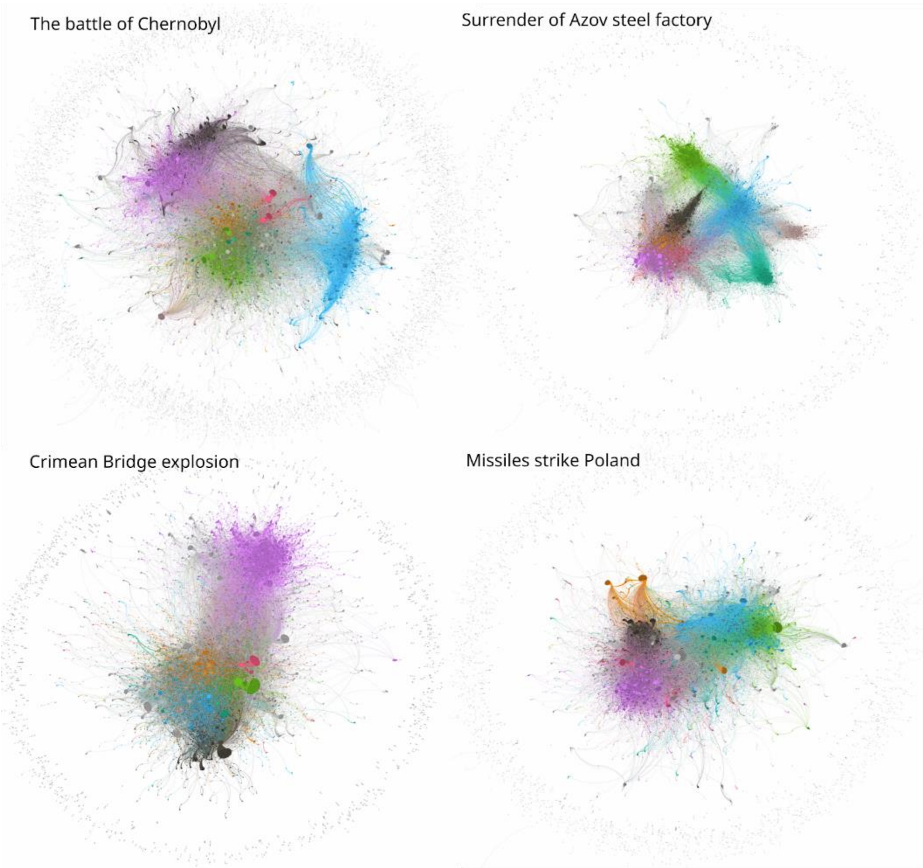
The Battle of Chernobyl Power Plant was one of the first war events that took place in the war. It was widely discussed in the media and reached a massive audience. The next event took place three months later. It was associated with the well-known Azov Brigade which surrendered to Russia after a few weeks of heavy fights. The partial destruction of the Crimean Bridge was one of the important war events of early autumn. This blocked the Russian ammo supply chains towards Crimea. Finally, in November two missiles hit Eastern Poland. Shortly after the incident, the situation was highly tense, as there was a suspicion that Russia attacked NATO borders. Later, it appeared

that the missiles came from the Ukrainian air defense system. Further details for these events can be found in footnotes.
To build the adjacency matrix, tweets with retweet count > 0 were selected together with messages that mention other Twitter user(s). Retweet is a re-posting of a Tweet. Twitter's Retweet feature helps users quickly share Tweets with all followers. In turn, mentions are Tweets that contain another person's username anywhere in the body of the Tweet. The mentioned people see tweets, where their username appears. Therefore, we were able to obtain nodes and edges of Tweets networks. Figure 1 presents the evolution of the number of tweets for a given war event in a longer period (48-36 hours). There are some differences in cascades but the peak is clearly visible and observed close to the historical time of the event.



**The vertical line is the time when the event historically occurred.*
Fig 1. The evolution of tweets cascade over time for selected war events in Ukraine*

In figure 2, we plotted these four networks together with detected communities which were marked with different colors. We applied Blondel et al. (2008) algorithm which looks for the nodes that are more densely connected together than to the rest of the network. The method is very fast and applicable for large networks.



**the larger the circle, the more influential the user is; colors mean communities: groups of nodes that are highly connected to each other but minimally connected with nodes outside their group*

Fig 2. Tweets network and communities for selected war events

The algorithm ranked 8 largest communities in these networks. In the case of the battle of Chernobyl, they contributed about ~34% of all tweets with the largest community input equal to 9% of Tweets. Regarding the Surrender of Azov Steel Factory the communities contribution was 71% of tweets with the largest group share equal to 19% of Tweets. 64% of all Tweets referring to both the Crimean Bridge explosion and Missiles strike Poland were produced by eight most influential communities. The largest groups for these events contributed respectively 16% and 18% of all Tweets. Rising contribution of communities in network formation may be the results of polarization and homophily as shown by Freelon et al. (2015) for the war in Syria.

Table 2. Characteristics of networks for selected war events.

network	nodes	edges	distance (mean)	diameter	closeness (mean)
The battle of Chernobyl	209279	300302	1.57	8	0.72
Surrender of Azov steel factory	95174	213210	3.88	18	0.51
Crimean Bridge explosion	128405	278353	3.22	12	0.50
Missiles strike Poland	150381	237196	1.77	7	0.67

3 Method

3.1 Tweets based Exponential Random Graphs Models

We used a social network theory framework (e.g. Wasserman and Faust, 1994; Hellmann and Staudigl, 2014) to model and simulate the networks. Graph models have a long tradition in social sciences and are used to study network structure and patterns as well as the evolution of the system over time (Hellmann, and Staudigl, 2014). One family of graph models is Exponential Random Graphs Models (ERGM) which belongs to the most widely-studied and universal network models (Snijders et al., 2006).

Exponential random graph models (ERGMs) are a class of statistical models used to analyze network data. They were first introduced in the late 1980s and early 1990s by statisticians such as Frank Holland (Holland & Leinhardt, 1981), Kathryn Roeder, and Peter Snijders (Snijders, 2001) and have its origins in spatial statistics and network theory (GOODREAU et al. 2009). They extend previous random graph models for social networks by more realistic construction of the structural foundations of agents' behavior (Robins et al. 2007). The basic idea behind ERGMs is to model the probability of observing a particular network structure (e.g. a set of nodes and edges) as a function of a set of covariates (e.g. node attributes) and network-based statistics (e.g. the number of triangles in the network).

One of the key features of ERGMs is that they allow for the modeling of network-level dependencies, such as the tendency for nodes to form triangles or other types of cliques. This is in contrast to traditional models for network data, such as the Erdős–Rényi random graph model (Frank, Strauss & Ikeda, 1986), which do not capture these types of dependencies.

ERGMs have been used to study a wide variety of social, biological, and technological networks, including online social networks, sexual networks, and protein-protein interaction networks. They have also been used to study various network-level phenomena such as homophily, triadic closure, and the formation of communities (Wasserman & Pattison, 1996).

Its purpose is to explore local forces that shape the global structure of the network () with two basic types of processes: dyad dependent and dyad independent. The former refers to the processes in which the state of one dyad depends on the state of another dyad(s). The latter comes with no dependence between dyads (Saha & Begum, 2015).

Formally, our Tweets' networks are defined as G = (V,E), where V are vertices (Twitter users) and E are edges (Tweets). The Tweets networks are directed, which means that this is a directed link from i to j $(i,j) \in E(G)$. The general model of this type could be expressed in log-linear form Hunter et al. (2008):

$$P(Y=y|n)= \frac{\exp(\theta g(y))}{k(\theta)} \quad (1),$$

where θ is the vector of model coefficients; Y is the space of possible graphs; g(y) is the vector of endogenous network's terms and k(θ) is the space of all possible graphs. Formula represents the probability of a set of ties (tweets) Y, having the number of nodes (users) n and their attributes. An alternative specification of the model can be expressed in log form:

$$\log(\exp(\theta' g(y)))=\theta_1 g_1(y)+\theta_2 g_2(y)+\ldots+\theta_p g_p(y) \quad (2),$$

Having in mind (1), the probability of a formation of single tie (dyad) can be formulated as the following logit equation:

$$\text{logit}=(Y_{ij}=1|n,y_{ij}^c)=\theta'\delta(y_{ij}) \quad (3).$$

y_{ij}^c represents all dyads different that Y_{ij}. The interpretation of model parameters is therefore similar to the logistic regression: shows contributions to the log-odds of single tie formation, having other connections unchanged. However, the coefficients obtained from an ERGM model may not be easily interpretable in terms of the underlying mechanism generating the network, as they do not necessarily imply causation but rather that the covariate or network statistic is associated with the network structure in some way (Hunter & Handcock, 2006).
A positive coefficient for a covariate indicates that the presence or increase of that variable is positively associated with the likelihood of the observed network structure. In contrast, a negative coefficient indicates that the presence or increase of that variable is negatively associated with the likelihood of the observed network structure (Robins, Pattison, Kalish, & Lusher, 2007; Carter & von Oertzen, 2018; Koskinen & Lusher, 2019).

3.2 Model simulations

Two methods can be used for estimation of network models of this type: maximum pseudo-likelihood estimation (MLE) and Markov chain Monte Carlo (MCMC) simulation. As our models contain several dyad dependent terms, the model parameters must be fit using MCMC simulation (Hunter and Handcock, 2008a). MCMC algorithm runs several simulations to find approximate MLE coefficients. The most common MCMC algorithm used for estimating ERGMs is the Metropolis-Hastings algorithm, which is a specific implementation that is well suited for ERGMs. The Metropolis-Hastings algorithm generates a sequence of samples from the posterior distribution of the parameters by proposing new parameter values and accepting or rejecting them based on the likelihood of the data given the proposed values (Ross, 2013). The algorithm is suitable for simulating networks containing several thousand nodes, however, the large number of edges is more problematic (Handcock et al. 2008b) and may induce very high computational costs (Tie et al. 2022). Our networks are very large also in terms of edges, therefore, it took substantial time to fit the models.
In computations, we used software implementation available in the 'ergm' R package which provides a collection of functions to plot, fit, diagnose, and simulate from exponential-family random graph models (Handcock et al. 2022). The loops (self-partnerships) and nodes without connection were deleted from graphs used for computations. We tried to capture networks' differences with regard to the desensitization hypothesis, but we were limited by metadata collected together with the tweets. On a basis of data availability, we decided to include the following measured variables to the models (table 3).

Table 3. Network variables used in MCMC simulations

observed variable	measure
Number of edges	What is the probability of forming a tie?
Number reciprocated tweets (mutual connections)	How likely are users to respond to the Tweets (if they are mentioned)?
Number of likes	How does tweet probability depend on the number of likes?
Number of quotations	How does tweet probability depend on the number of quotations of the Tweet? (communities formation, interactions between users?)
Number of retweets	How does tweet probability depend on the number of retweets for the given war events?

Language of the tweet (homophily term)	Do Twitter users have a tendency to form a tie within the same language group?

Eight most frequent Tweets' languages were included into the models for each of the events. The result is that there are some slight changes in categories - some languages were present in one network and absent in others. However, three languages (besides English) that qualified as a separate category for all networks were: Spanish, French and Japanese. Remaining 4 languages differ with regard to graphs and were neither presented nor considered in the interpretation of results.

3.3 Results, diagnostics, evaluation

The coefficients of an exponential random graph model represent the strength and direction of the relationship between the network structure and the covariates or network statistics included in the model. The models converged properly; the number of needed iterations differed between six to eleven. Before analysis we visually assessed the trace plots from the final iteration of the MCMC chain. They did not show the symptoms of model degeneracy (the sampled values had a bell-shaped distribution and were centered at zero). Further goodness-of-fit diagnostics is presented in the next subsection (4.4). In Table 4 we presented the results of the simulations. Coefficients were given in log odds. To obtain probabilities associated with given parameters we exponentiated them according to the formula: $\exp(\theta)\,/(1+\exp(\theta))$.

Table 4. Results of the MCMC simulations of ERGM

network/ variables	Battle of Chernobyl	Surrender of Azov steel factory	Crimean Bridge explosion	Missiles strike Poland
edges	0.00008*** *(0.000)*	0.00002*** *(0.000)*	0.00006*** *(0.000)*	0.00001*** *(0.000)*
mutual	0.9750*** *(0.000)*	0.9776*** *(0.000)*	0.8633*** *(0.000)*	0.9895*** *(0.000)*
likes	0.4996*** *(0.000)*	0.5000* *(0.010)*	0.4998* *(0.022)*	0.4999 *(0.20)*
quotes	0.4998 *(0.118)*	0.4934*** *(0.000)*	0.4990* *(0.022)*	0.4998** *(0.004)*
retweets	0.4999*** *(0.000)*	0.5000*** *(0.000)*	0.4999*** *(0.000)*	0.5000*** *(0.000)*
nodematch: language	0.4949*** *(0.000)*	0.4922*** *(0.000)*	0.2513** *(0.003)*	0.5068 *(0.435)*

Spanish	0.4567*** *(0.000)*	0.5312*** *(0.000)*	0.1713*** *(0.000)*	0.4010*** *(0.000)*
French	0.5802*** *(0.000)*	0.6177*** *(0.000)*	0.1408*** *(0.000)*	0.3914*** *(0.000)*
Japanese	0.4682*** *(0.000)*	0.4229*** *(0.000)*	0.1696*** *(0.000)*	0.6217*** *(0.000)*
AIC BIC	6170301 6170590	2920509 2920773	3235595 3235863	4695393 4695694
MC Std. Err.	1.032	2.138	0.372	3.576
p-value*	0.71	0.49	0.34	0.37

**joint p-value from the last round of simulation, prior to computation of final parameter estimates.*

The joint p-values are computed for the differences between observed networks and those from the simulated networks. A low p-value suggests that there may be a problem with the fit for that graph statistic. The probabilities above 0.5 are associated with positive log-odds and positive effect on tweet formation while the probabilities below 0.5 indicate negative log-odds and negative effect on tweets formation.

There is strong and significant mutuality effect in all presented networks. The probability of tie reciprocation is between 0.86 and 0.99 which corresponds with log-odds between 2 and 4.5. It means that if one user put the other user username in a tweet it is highly probable that this mentioned user will reciprocate the tweet and contribute the network statistics. The probability was very high and significant for all networks (a little bit lower for the Crimean Bridge explosion). However, we have also found some evidence supporting the social desensitization hypothesis:

- the overall number of significant model parameters drops as we consider later war events. It means that together with time, fewer Tweeter characteristics impact formation of new comments.
- significance of *the number of likes* decreases as we consider later war events. It means that users pay less attention to reaction of other users and this reaction not necessarily induce new comments.
- overall significance of *language* decreases. It means that users less likely respond to comments produced during later war events.
- significant and negative effects of Spanish and French comments on tweet formation (probability < 0.5; log odds = -1.70). The effect is stronger for later war events. It means that users of the most popular languages are less likely to form a tie.
- very slight but negative effect of *the number of quotes* on tweet formation that is observed for later war events (probability < 0.5, log odds = -0.02). It means that raising the number of quotations decreases the probability of tweet formation.

MCMC-based estimation for ERGM models have found that the algorithms often converge to degenerate graphs – graphs that are either empty or complete. If the model is a good fit to the observed data, then networks drawn from this distribution will be more likely to "resemble" the observed data. To evaluate the goodness-of-fit for our model, we need to simulate many variations of the model from the probability distribution defined by the model's parameters.

If the model is a good fit, the networks drawn from this distribution should be similar to observed. Goodness-of-fit is presented in figure 3. It shows boxplots of the simulated counts together with observed graph statistics. This provides a quick sanity check of the quality of the model.

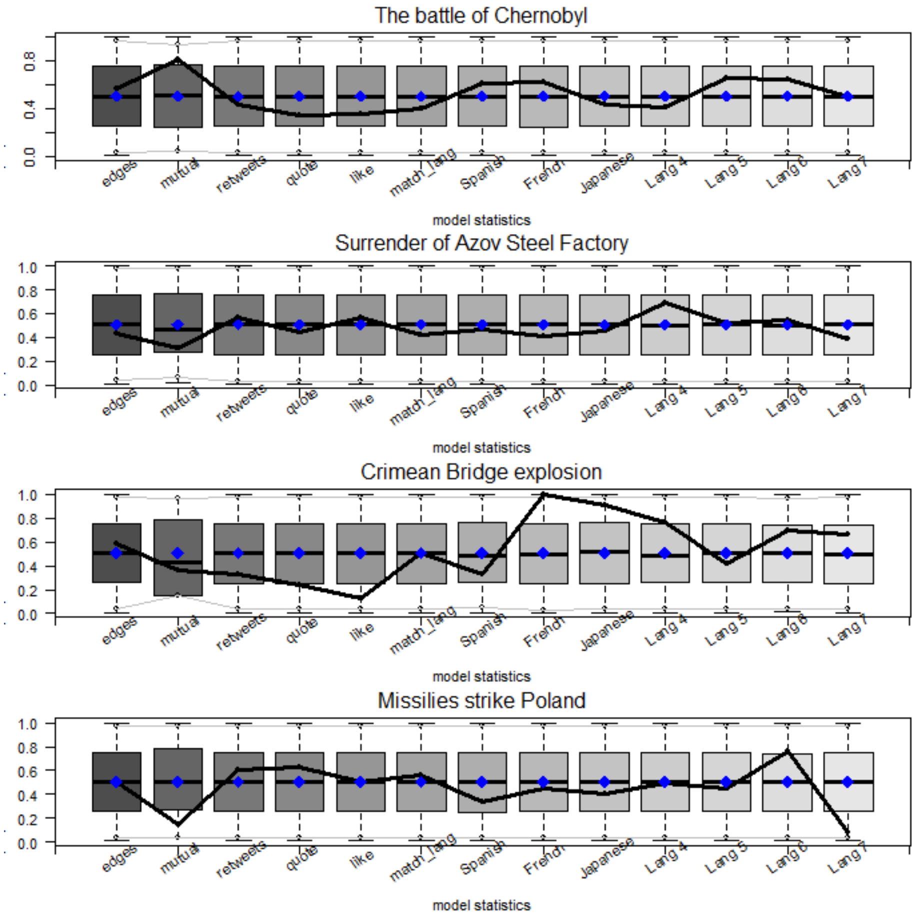


Fig. 3. Simulated vs empirical network statistics

The diagnostic plot suggests good mixing, and the distribution of the sample statistic deviations from the targets suggest that simulations from the models mostly fit the target values. There are some problems with languages parameters in Crimean Bridge explosion network (French) and missiles strike Poland (Lang 7). In these cases the sampled values reach maximum/minimum threshold.

4 Conclusion

Exposure to news and videos both on traditional and social media can lead to decreased empathy towards victims and increased tolerance for violence. The rapid and widespread dissemination of such news through new media (like Twitter) can exacerbate these effects, as individuals are constantly exposed to graphic content without the necessary emotional processing time. The implications of social desensitization could be reduce willing to support people in need as well as compassion fatigue. These processes together with large-scale organized disinformation strategies could be hidden supporter of ongoing Russian invasion.

Under this framework, the paper presents a network study of Tweets dissemination during the war in Ukraine and verifies the social desensitization hypothesis. In the study, we investigated if together with the time of the invasion, people became less sensitive to war events. We collected thousands of Tweets regarding four selected war events that took place in various time points between February 2022 and November 2023. We developed exponential random graph models that were estimated with MCMC simulation and verify how likely people engage in producing and sharing the comments regarding these events.

The strongest predictors of tie formation are structural: a tie is most likely to be formed if it would reciprocate an existing tie or it is related to a mutual acquaintance. This is constant for all developed network models. However, we have confirmed that Twitter users become less likely to produce and share comments regarding war events in Ukraine over time: the number of significant parameters drops as we consider later events; there is also a decrease in probability of tie formation for some homophily terms (mainly language and the number of likes).

We have also identified rising contribution of communities to the total number of Tweets. This may indicate polarization of opinions, induce intra-group homophily, support propaganda, and spread of fake news as pointed out in several existing studies (Coscia, Rossi, 2022). Such networks bases on cultivating its own audience and long-run social impact is unknown.

Luckily, social desensitization is fully reversible as we can effectively use social media to induce empathy and humanize victims of tragic events by providing the wider context of theirs commonplace concerns (Roberts, 2021). Overgaard and Woolley (2022) suggest that Twitter should support exposure to tweets from account of outgroup contact as well as prioritize comments that are popular among different groups and encourage confrontation of opinions.

References

1. Begum, Munni & Saha, Sudipta. (2015). A Comparative Analysis on Computational Methods for Fitting an ERGM to Biological Network Data. Network Biology. 5. 1-12. 10.0000/issn-2220-8879-networkbiology-2015-v5-0001.
2. Brockmyer, J. F. (2013). Media violence, desensitization, and psychological engagement. In K. E. Dill (Ed.), The Oxford handbook of media psychology (pp. 212–222). Oxford University Press.
3. Cocking, C., Drury, J., & Reicher, S. (2009). The nature of collective "resilience": survivor reactions to the July 7th (2005) London bombings. International Journal of Mass Emergencies and Disasters, 27(1), 66-95.
4. Coleman, A. & Shayan Sardarizadeh, Ukraine war: Viral conspiracy theories falsely claim the war is fake, https://www.bbc.com/news/world-europe-64789737
5. Coscia M, Rossi L (2022) How minimizing conflicts could lead to polarization on social media: An agent-based model investigation. PLoS ONE 17(1): e0263184. https://doi.org/10.1371/journal.pone.0263184
6. De Choudhury M, Jhaver S, Sugar B, Weber I. Social Media Participation in an Activist Movement for Racial Equality. Proc Int AAAI Conf Weblogs Soc Media. 2016 May;2016:92-101. PMID: 28840078; PMCID: PMC5565729.
7. Fanti, K.A., Vanman, E., Henrich, C.C. and Avraamides, M.N. (2009), Desensitization to media violence over a short period of time. Aggr. Behav., 35: 179-187. https://doi.org/10.1002/ab.20295
8. Frank, O., Strauss, D., & Ikeda, J. (1986). Markov graphs. Journal of the American Statistical Association, 81(396), 832–842.
9. Gentile, D.A., & Bushman, B.J. (2012). Reassessing media violence effects using a risk and resilience approach to understanding aggression. Psychology of Popular Media Culture, Vol. 1, No. 3.
10. Goodreau SM, Kitts JA, Morris M. Birds of a feather, or friend of a friend? Using exponential random graph models to investigate adolescent social networks. Demography. 2009 Feb;46(1):103-25. doi: 10.1353/dem.0.0045. PMID: 19348111; PMCID: PMC2831261.
11. Handcock M, Hunter D, Butts C, Goodreau S, Krivitsky P, Morris M (2018). _ergm: Fit, Simulate and Diagnose Exponential-Family Models for Networks_. The Statnet Project R package version 3.9.4, <https://CRAN.R-project.org/package=ergm>.
12. Hellmann T., Mathias Staudigl, Evolution of social networks, European Journal of Operational Research, Volume 234, Issue 3, 2014, Pages 583-596, https://doi.org/10.1016/j.ejor.2013.08.022.
13. Holland, P. W., & Leinhardt, S. (1981). An exponential family of probability distributions for directed graphs. Journal of the American Statistical Association, 76(373), 33–50.
14. Hunter D, Handcock M, Butts C, Goodreau S, Morris M (2008). “ergm: A Package to Fit, Simulate and Diagnose Exponential-Family Models for Networks.”, Journal of Statistical Software, 24(3), 1-29.
15. Krahe, B., Moller, I., Kirwil, L., Huesmann, L.R., Felber, J., & Berger, A. (2011). Desensitization to media violence: Links with habitual media violence exposure, aggressive cognitions, and aggressive behavior. J. of Personality and Social Psychology, Vol. 100, No. 4.
16. Maireder, A., Weeks, B. E., Gil de Zúñiga, H., & Schlögl, S. (2017). Big Data and Political Social Networks: Introducing Audience Diversity and Communication Connector Bridging Measures in Social Network Theory. Social Science Computer Review, 35(1), 126–141. https://doi.org/10.1177/0894439315617262

17. Moeller, S, D, (1998). Compassion Fatigue How the Media Sell Disease, Famine, War and Death, Routledge.
18. Mrug S, Madan A, Cook EW 3rd, Wright RA. Emotional and physiological desensitization to real-life and movie violence. J Youth Adolesc. 2015 May;44(5):1092-108. doi: 10.1007/s10964-014-0202-z.
19. OECD, 2022, Disinformation and Russia's war of aggression against Ukraine: Threats and governance responses, https://www.oecd.org/ukraine-hub/policy-responses/disinformation-and-russia-s-war-of-aggression-against-ukraine-37186bde/
20. Overgaard, Ch. S.,Woolley, S. (2022), How social media platforms can reduce polarization, Brookings Tech Stream, https://www.brookings.edu/techstream/how-social-media-platforms-can-reduce-polarization/
21. Robins, G. Pip Pattison, Yuval Kalish, Dean Lusher, An introduction to exponential random graph models for social networks, Social Networks, Volume 29, Issue 2, 2007, Pages 173-191, https://doi.org/10.1016/j.socnet.2006.08.002.
22. Roberts, J. (2021). Empathy Cultivation through (Pro)Social Media: A Counter to Compassion Fatigue. Journalism and Media, 2(4), 819–829. MDPI AG. Retrieved from http://dx.doi.org/10.3390/journalmedia2040047
23. Ross, S. 2013, Chapter 12 - Markov Chain Monte Carlo Methods, Editor(s): Sheldon Ross, Simulation (Fifth Edition), Academic Press, 2013, Pages 271-302, https://doi.org/10.1016/B978-0-12-415825-2.00012-7.
24. Russo C., Prashant Aukhojee, Brooke McQuerrey Tuttle, Olivia Johnson, Mark Davies, Brian A. Chopko, Konstantinos Papazoglou, 7 - Compassion fatigue & burnout, Editor(s): Konstantinos Papazoglou, Daniel M. Blumberg, POWER, Academic Press, 2020, Pages 97-115, https://doi.org/10.1016/B978-0-12-817872-0.00007-0.
25. Sanchez, Barbara C. (2020) "Internet Memes and Desensitization," Pathways: A Journal of Humanistic and Social Inquiry: Vol. 1 : Iss. 2 , Article 5. https://repository.upenn.edu/pathways_journal/vol1/iss2/5
26. Snijders, T.A.B., Pattison, P.E., Robins, G.L. and Handcock, M.S. (2006), NEW SPECIFICATIONS FOR EXPONENTIAL RANDOM GRAPH MODELS. Sociological Methodology, 36: 99-153. https://doi.org/10.1111/j.1467-9531.2006.00176.x
27. Snijders, T. A. (2001). The statistical evaluation of social network dynamics. Sociological Methodology, 31(1), 361–395.
28. Shoshani, A. & Michelle Slone (2008) The Drama of Media Coverage of Terrorism: Emotional and Attitudinal Impact on the Audience, Studies in Conflict & Terrorism, 31:7, 627-640, DOI: 10.1080/10576100802144064
29. Tie, Z., Zhu, D., Hong, S., & Xu, H. (2022). A Hierarchical Random Graph Efficient Sampling Algorithm Based on Improved MCMC Algorithm. Electronics, 11(15), 2396. https://doi.org/10.3390/electronics11152396
30. Wasserman, S., & Faust, K. (1994). Social Network Analysis: Methods and Applications (Structural Analysis in the Social Sciences). Cambridge: Cambridge University Press. doi:10.1017/CBO9780511815478
31. Zhang, B., Semenov, A., Vos, M., & Veijalainen, J. (2014). Understanding Fast Diffusion of Information in the Social Media Environment. A Comparison of Two Cases.. In C. M. Genest (Ed.), *CCI 2014 : Proceedings of the Conference on Corporate Communication 2014* (pp. 522-533). Corporate Communication International.
32. Wasserman, S., & Pattison, P. (1996). Logit models and logistic regressions for social networks: I. An introduction to Markov graphs and p*. Psychometrika, 61(3), 401–425.