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ARTICLE

Russia's Online Opposition Communities Before and During the Special Military Operation

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ABSTRACT
The authors mapped two clusters of communities that were most active in supporting the opposition discourse on VK, a Russian social network, in the spring of 2021 and the spring of 2024. This work was driven by the aspiration to reveal the ideological guidelines of opposition-minded netizens and measure the level of their political mobilization. A cross-temporal approach was instrumental in understanding how the historical and political context, including the Ukraine conflict, influenced the willingness and readiness of online communities to generate protests. The authors proposed a mobilization index based on self-organized criticality, a theory which has its origin in natural science. The 2021 cluster included 268 communities and consisted mainly of the liberal opposition, which, at that time, tried to urge its followers to take to the streets. Approximately 13% of the communities demonstrated a high level of mobilization. Over the next two years, the core of this liberal protest infrastructure ceased to exist online. Courts and prosecutors dismantled the majority of mobilized and influential communities. The 2024 cluster, which consisted of 200 communities, emerged as a reflection of the discussion about the strategic goals and tactics of the special military operation (SMO). The liberal segment still existed, though such communities demonstrated a minimal level of mobilization. Russian nationalists dominated the 2024 cluster. Many of their communities (approximately 27%) have mobilized and effectively influenced the opinions, views, and motivation of other users. The SMO has led to a change in the dominant ideas that shape the opposition discourse online. Liberal talking points have lost the initiative, and now that initiative has been seized by nationalist talking points, which are focused on winning the SMO, intensifying military

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operations, and “eradicating internal enemies” including pro-Western liberals and migrants.

KEYWORDS
social networks, politicized communities, Russia, theory of self-organized criticality, political mobilization

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Purpose and Object of Study

The key research question for this study is as follows: How have changes in domestic and international politics—primarily related to the special military operation (SMO)—influenced the status and activity of politicized online opposition communities on VK[1], the most popular Russian social networking service? We sought to understand whether these communities had and still have the ability to mobilize their members for political demonstrations. We focused on two network clusters comprising interconnected nodes (communities) that were most active in promoting the opposition discourse online in 2021 (before the SMO) and in 2024 (more than two years into the SMO). Within the mapped clusters, three conglomerates of communities could be distinguished, each offering a disparate vision of Russia’s future and interpretation of current politics: liberals, Russian nationalists, and communists (along with Stalinists). We also considered it necessary to account for communities belonging to such conglomerates as “Doomscrollers” (those who read shocking and low-quality news) and “Junk Information” (eclectic politicized groups). Communities of these types often play the role of intermediaries in online communication.

Our study was not only limited to communities dedicated exclusively to politics (e.g., official VK communities of political parties). We regarded communities where the members regularly express their political views (both in posts and in comments) as politicized, irrespective of the main topic of the communities.

In this study, mobilized communities are understood as groups composed of members who are strongly disposed to assimilate and share community messages and whose political views and willingness to act, both in virtual reality and real-world spaces, are shaped by such messages. Members of mobilized communities are tightly involved in community life, actively communicate (read and share messages, react to them), and put trust in community ideas and feel engaged in them through their views, opinions, and calls to action. Mobilized communities are an effective mechanism for the dissemination of some political messages, usually via reposting. Additionally, they are ready to respond to calls within the community, including bids to take to the streets.

[1] VK (short for its original name VKontakte) is a Russian online social media and social networking service. https://vk.com VK™ is a trademark of VK.com Ltd.

Approach and Literature

Engagement, trust, involvement, and willingness to act are rather elusive phenomena. These concepts are especially difficult to spot and measure in the online environment, which is replete with communities that have artificially inflated indicators and can, at best, only spark a short-lived superficial interest from users. Traditional sociological tools, albeit providing reliable results, are too resource-intensive for a quick survey of hundreds of groups.

In order to identify mobilized communities, we put forward an indicator based on the theory of self-organized criticality (SOC), a concept that originally emerged in natural science. This interdisciplinary concept describes the complex dynamics of some systems at the macro level as a result of many ordinary events at the micro level—in our case, actions of users. Thus, the proposed indicator makes it possible to discern the type of behavior of participants in aggregate data on community dynamics.

SOC is a special state of some systems; a kind of bifurcation point extended in time. SOC emerges only in systems where numerous elements or participants actively reflect the states of each other and the entire system in feedback loops. Here, even local, short-lived, and weak impulses or events initiate such cause-and-effect chains that do not fade quickly enough and can, therefore, spread across the entire system. Mutual reinforcement and weakening of many cause-and-effect chains cause oscillations of different scales in the system, or pink noise (1/f-noise). One of the founders of the SOC theory, Per Bak, described it as follows:

> A phenomenon called *1/f* (one-over-*f*) noise has been observed in systems as diverse as the flow of the river Nile, light from quasars … and highway traffic … There are features of all sizes: rapid variations over minutes, and slow variations over years … The signal can be seen as a superposition of bumps of all sizes; it looks like a mountain landscape in time, rather than space. The signal can, equivalently, be seen as a superposition of periodic signals of all frequencies. This is another way of stating that there are features at all time scales. Just as Norway has fjords of all sizes, a 1/*f* signal has bumps of all durations … One-over-*f* noise is different from random white noise, in which there are no correlations between the value of the signal from one moment to the next. (Bak, 1996, pp. 21–22)

A system in the state of SOC is prone to avalanches without clear immediate causes. This can occur due to sudden bursts of activity or strong and quick deviations of key parameters from the norm.

In recent years, studies have appeared confirming the presence of SOC in some sociopolitical processes, particularly in network processes. Pink noise is described in various systems: physical, biological, social, etc. The SOC theory equates pink noise with punctuated equilibrium, which has been described in many scientific fields. In this case, the system has the dynamic in which periods of rest of varying duration are followed by bursts of activity of different scales, including the most dramatic surges, named avalanches. As Malinetskii (2013) puts it, punctuated equilibrium can be observed in the course of biological evolution as well as in the functioning of social and technical systems. As a rule, nothing noticeable happens for a very long time until a sudden change radically alters the appearance of the system, and a time of revolution arrives, which certainly does not negate the multitude of minor events which are just left unnoticed (p. 39).

Several studies indicate that online communities in a state of SOC should be viewed as mobilized and characterized by a high level of participant engagement (Açıkalın & Artun, 2019; Dmitriev & Dmitriev, 2021; Tadić et al., 2017; Zhukov & Lyamin, 2017). A close and active interaction between participants generates SOC effects. Such online communities can quickly, and without any apparent compelling reason, become excited. They resemble an enlivened crowd that is ready to let loose at any moment and create a data avalanche of demands, opinions, and views. Such an avalanche can cross the fine line between virtual anger and non-virtual political activism.

Thus, in this study, we used an attribute of the state of SOC—pink noise—as an indicator of mobilization. This indicator is calculated based on time series containing data on the variation of some important system parameters over time. We believe that repost activity in the community is the most relevant parameter. Reposting is a fundamental act of online reflection, that is, reception and transmission of messages. Therefore, reposting activity directly indicates the level of reflexivity of communities, their ability to emit, perceive, and reflect (as well as multiply) network messages.

The concept of self-organized criticality was introduced in 1988 (Bak et al., 1988). Later, in 1998, Roberts and Turcotte (1998) presented empirical evidence suggesting the presence of SOC dynamics in political processes, particularly in the global dynamics of military conflicts. The application of SOC in the social sciences was further advanced by Malinetskii (2013), a prominent proponent of interdisciplinary synergetics. Similarly, Borodkin (2019) called on the scientific community to explore the heuristic potential of SOC in historical research.

In 2001, Podlazov explored possible applications of the ideas of SOC to the clarification of social research problems (Podlazov, 2001). Brunk (2001) made a significant contribution to the development of SOC within the domain of social sciences by proposing that SOC underlies major historical upheavals. Kron and Grund (2009) likewise argued that SOC is a widespread phenomenon in history. Maulana and Situngkir (2010) identified markers of SOC in electoral outcomes in Indonesia, Mexico, Brazil, and India, suggesting that political systems may operate under SOC dynamics. Shimada and Koyama (2015) hypothesized that the presence of SOC indicators in political behavior reflects the accumulation of transformational potential within society.

The theory of SOC has been applied across a wide range of topics in the social sciences: extremism and terrorism (Picoli et al., 2014), corporate governance (Thietart, 2016), collective knowledge production in online communities (Tadić & Melnik, 2021; Tadić et al., 2023), political mobilization on social media (Aguilera et al., 2013; Dmitriev & Dmitriev, 2021; Dmitriev et al., 2023; Zhukov & Lyamin, 2017), protest movements (Açıkalın & Artun, 2019), political journalism (Latonov & Latonova, 2022), and domestic political conflict (Schulte & Trinn, 2024; Trinn, 2018; Trinn & Naumann, 2023).

Lu et al. (2021) demonstrated that the theory of SOC can be used to model the rise and fall of empires across centuries of Chinese history. More recently, Banerjee, Biswas, Chakrabarti, Challagundla, et al. (2023) and Baherjee, Biswas, Chakrabarti, Ghosh, & Mitra (2023) argued that SOC mechanisms constitute the root cause of persistent social inequality.

The diverse manifestations of SOC in social reality have prompted efforts to clarify the philosophical status of the theory within contemporary scientific paradigms (Golovashina, 2017; Zhukov, 2022).

Problems

The mobilization of online communities has become a focus of research for two fundamental reasons. Firstly, it is believed that mobilized communities can push their members to transgress the boundary separating the realm of opinion from that of action. Therefore, there is a need to identify communities capable of inciting street protests at a precarious time.

Secondly, it is assumed that mobilized communities can influence the online political agenda because they have the power to shape the thinking of their members and the online environment. This makes such communities a useful tool for refocusing public attention despite the effort of mainstream media concerning dissemination of information.

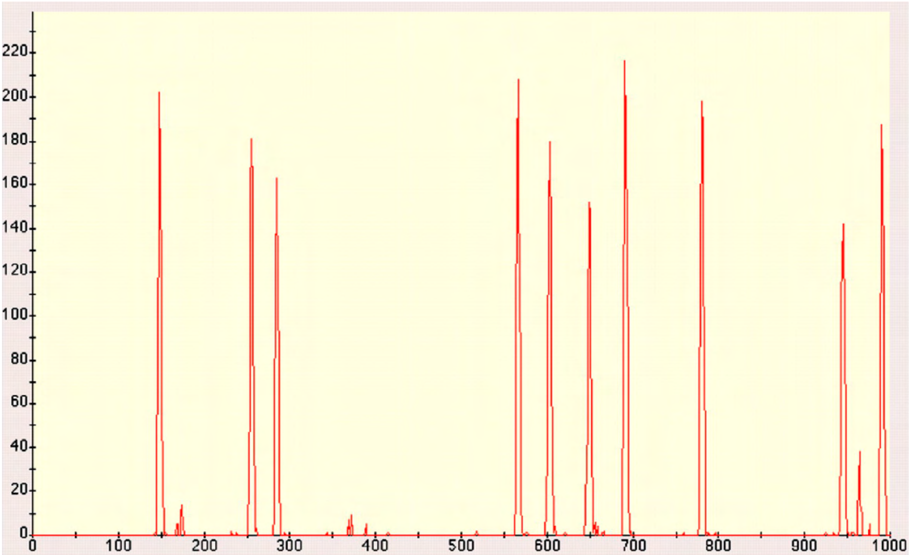
However, there are considerable challenges in finding solutions to research problems and political issues associated with online mobilization. Despite unprecedented accessibility, networks are very opaque for researchers. Social media is replete with fake accounts, as well as accounts, activities, and communities with artificially inflated indicators. Further, it is difficult to pinpoint such subtle phenomena as engagement, trust, and unanimity. However, communities that can influence and motivate are precisely the ones capable of evoking such feelings in users. Within an enormous flow of noisy data, how can we identify communities that evoke engagement in a substantial number of people? This research situation has necessitated the tools of the SOC theory.

Over the last two decades, several papers have considered punctuated equilibrium as an attribute of contemporary protest movements (both online and on the streets). Meanwhile, the SOC theory tends to treat punctuated equilibrium as pink noise. Punctuated equilibrium is a common, counter-intuitive, and very powerful phenomenon.

The creator of one of the first agent-oriented models of protest activity, Epstein (2002), drew attention to the strange dynamics of protest activity through computational experiments. In his experiments, he reproduced the effects of SOC using a variety of simulation models, most of which were agent-oriented. For example, a key model in SOC theory is a pile of sand.

Epstein's model was published in 2002 in *Proceedings of the National Academy of Sciences* thus setting the style for research into modern protest movements and color revolutions (Figure 1). These phenomena are often treated as nonlinear effects, as manifestations of a borderline state between chaos and order.

Figure 1
Punctuated Equilibrium in the Agent-Based Model of Epstein



Note. Source: Epstein, 2002.

Firstly, agents (people) interacting only with their immediate environment (in microgroups) can, in some cases, reach a mutual agreement regarding a change in the rules of the game or in the principles of behavior without the use of global communication tools such as a referendum. Secondly, the transition of agents to a new state can occur in an avalanche, i.e., tipping. Thirdly, the participants and carriers of this process can be agents for whom the undoing of the previous rules of the game was not a significant task. As Epstein (2002) notes, sometimes the general behavior of the system is entirely unexpected and would be quite hard to predict from the underlying rules of agent behavior. Fourthly, the transformation process is barely noticeable in the initial phases. It may be triggered by weak local impulses, whether those be random events or external influences. In some systems (including SOC systems), such impulses do not fade away completely or quickly enough, given they are preserved by the ordinary behavior/interests of actors. Fifthly, transformation processes can be reinforced in feedback loops (e.g., self-reflection of discontent, escalation of conflict, etc.).

A similar effect—blow-up—has been studied by Russian researchers. The social meanings of this concept are explained in Kapitsa et al.'s book *Sinergetika i Prognozy Budushchego* [Synergetics and Forecasts of the Future] (2001):

> For a long time … the function *T* hardly changes, it seems that nothing is happening at all. But near a [certain] moment in time … called the blow-up time, instability becomes explosive. The standard forecasting algorithm, which is still used in the social sciences—"calculate percentage by which the value has changed

> over the previous period of time … [and multiply] this percentage by the current value", [or] the famous planning technique "based on past performance"—is not applicable here." In modeling, blow-up makes one or more parameters of the system go to infinity. In the real world, such a situation usually means a phase transition—a transformation of the qualitative state. (p. 49; Trans. by Dmitry Zhukov, Sergey Lyamin, & Dmitry Seltser—D. Z., S. L., & D. S.)

Strange dynamics of protest demonstrations emerged in Epstein's computational experiments:

> Random spatial correlations of activists catalyze local outbursts. This is why freedom of assembly is the first casualty of repressive regimes … To be the first rioter, one must be either very angry or very risk-neutral, or both. But to be the 4,000th—if the mob is already big, relative to the cops—the level of grievance and risk-taking required to join the riot is far lower. This is how, as Mao Tse Tung liked to say, "a single spark can cause a prairie fire" … Coincidentally, the Bolshevik newspaper founded by Lenin was called *Iskra*, the spark!
> A time series of total rebels is also revealing. It displays one of the hallmarks of complex systems: punctuated equilibrium (Fig. 3). Long periods of relative stability are punctuated by outbursts of rebellious activity. And indeed, many major revolutions (e.g., East German) are episodic in fact.
> The same qualitative pattern of behavior—punctuated equilibrium—persists indefinitely… (Epstein, 2002)

The model shows that mass protests "arise from nowhere," without any connection to significant socioeconomic circumstances. Therefore, the initialization of institutional tipping is an effective but destructive technology. As modeling demonstrates, political systems that seem stable and centralized at first glance can be very vulnerable to political technologies that do not require any significant resources and often come down to creating the illusion of mass revolutionary sentiment. This is achieved when the connections between protest agents are reinforced and branched out, the connections between loyalists are destroyed, and state institutions are inadequate and slow in their response.

For example, Brichoux and Johnson (2002) summarize their work on revolutions as follows:

> Our simulation results show that when the probability of favorable government response is in a middle range, a few consistent activists can make the difference in a society ... We discussed a number of parameters in the agent-based model that can make the recipe "just so." … Success-motivated individuals will contribute to success only when their effort can be expected to matter. Sometimes the individuals can see too many others, or the regime is too resistant to change, and individuals who do see a few protesters will conclude that their own effort would be wasted in a losing cause. Under such conditions, a few activists can make a big difference.

> But their power to overcome perceptions of hopelessness is not without limits … The low regime resistance … produces a saturation effect; even a small amount of visible protest is sufficient to make agents believe that the probability of success is too high to make their contribution worthwhile. The result is small clusters of protest distributed fairly evenly across the grid. (Brichoux & Johnson, 2002)

In the model of revolution by Makowsky and Rubin (2013), a "shock" is required to trigger the process. A shock is an event that makes some agents reveal their (counter-system) preferences. A shock causes a revolutionary cascade, as an increasing number of agents follow suit. It is important that the cascade should reach some minimum required size:

> Our results suggest that highly centralized regimes may seem tranquil but are highly susceptible to revolution, especially in large network-range economies. These results shed light on the institutional, technological, and social mechanisms facilitating the recent spread of revolutionary activity in the Arab world, the rapid decline of the Communist bloc, and numerous other instances where regime change occurred rapidly and unexpectedly in centralized societies.
> An agent-based model highlights the role that information and communication technology (ICT) play in triggering cascades of preference revelation in centralized societies. We show that network range reduces the minimum shock that is sufficient to effect institutional change, and this result is exacerbated as centralization increases … ICT and preference falsification thus complement each other in the production of revolutionary activity; the former facilitates the transmission of the shock while the latter increases the magnitude of change that arises after a shock. (Makowsky & Rubin, 2013)

Until recently, researchers implicitly or explicitly assumed that such technologies were dangerous only for some "vicious" ("underdeveloped" and "corrupt") political institutions. Recently, a number of events, e.g., most notably the Yellow Vests protests in France (Le Goff, 2020) and the wave of violent mass protests in the United States during Trump's first term (Arnold et al., 2018), have shown that political institutions that were previously considered "exemplary" and "ideal" are also subject to tipping.

One of the reasons modern political institutions are sensitive to nonlinear transformation effects is, apparently, due to the fact that political processes now take place partly in virtual space. The Internet is not just a new means of communication, it produces qualitatively new political phenomena and/or fundamentally changes the traditional ones.

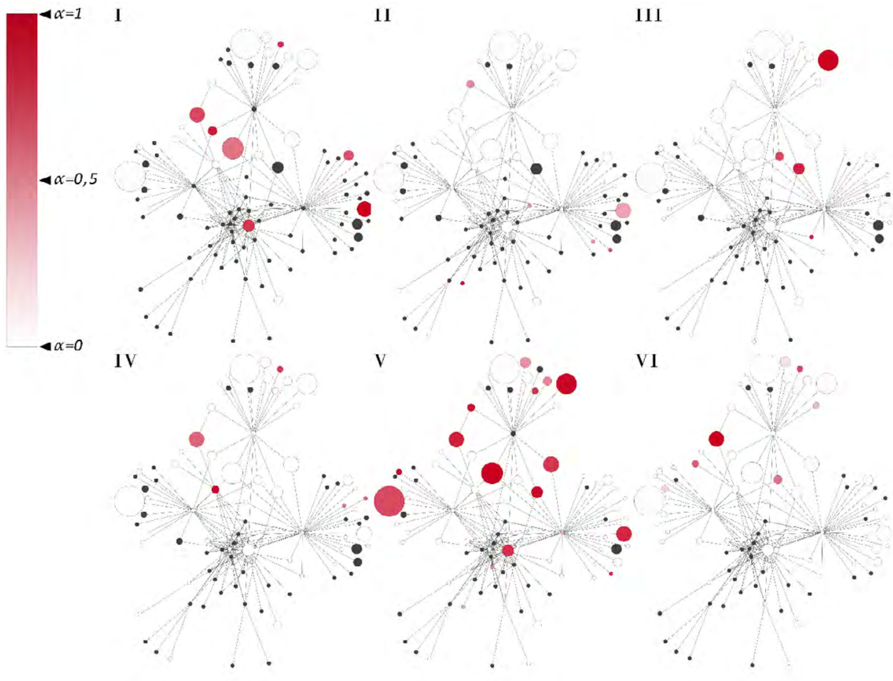
Among such phenomena, the one that, in our opinion, should be paid close attention to is data avalanches, and in particular, surges in reposts. Due to avalanches, community activity and the online presence of some messages enjoy an increase of several tens or often hundreds of times the average level. From the point of view of SOC theory, a data avalanche is essentially a nonlinear effect. A data avalanche is manifested in the disproportion between causes and effects, that is, the disproportion between news and its results. The immediate cause of an avalanche is not significant in itself. When a system is ready for avalanches, any insignificant message can serve as a trigger. A data avalanche occurs unexpectedly, without a clearly noticeable preparation period.

In our previous studies, we found empirical evidence that supports two hypotheses (Zhukov, 2022; Zhukov & Lyamin, 2017). First, data avalanches contribute to the escalation of online discontent to street violence. Second, data avalanches may be responsible for the swift and difficult-to-explain refocusing of public attention online.

The association between violent street actions and the emergence of pink noise in online protest communities was examined using the example of two online clusters (on Facebook[2] and VK), one of which supported the impeachment of Dilma Rousseff in Brazil in 2016 (Figure 2); the other the revolutions in Armenia in 2015 and 2018 (Figure 3). It was found that pink noise accompanied the political mobilization of virtual communities and data avalanches preceded street protests.

Figure 2

Pink Noise in the Network During the Period From January 1, 2015 to August 31, 2016 (Brazil, Facebook[2], Communities Protesting Against Dilma Rousseff)

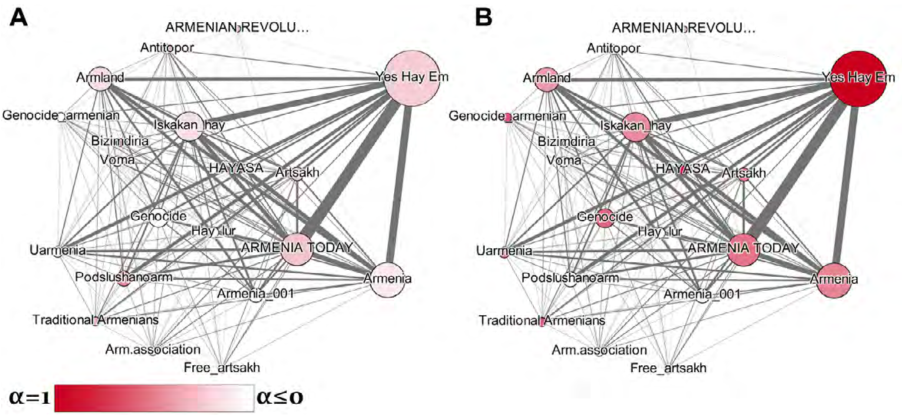


Note. Source: Zhukov & Lyamin, 2017.

[2] Facebook™ is a trademark of Facebook Inc., registered in the U.S. and other countries. По решению Роскомнадзора, социальная сеть Facebook в России признана экстремистской организацией и заблокирована.

Figure 3

Cluster of the Protest Network on VK From September 8, 2017 to January 6, 2018 (A) and From January 8, 2018 to May 8, 2018 (B)



Note. Source: Zhukov, 2022.

We assumed that, due to the swiftness and significant scale of avalanches, a "virtual crowd" effect occurs in many "overheated" communities. Rapidly mounting information pressure makes the members of online communities strongly believe that the whole society has been stirred and is inspired by one certain idea. In the works cited earlier in this section, such a feeling was considered an indispensable condition for the transition from protest moods to protest actions.

The political agenda is a crucial and, in some cases, determining factor in political processes. In this study, we examined one of the spaces in which the agenda exists, that is social media. The mechanisms of setting and changing the agenda in social networks remain a "black box." The idea that the political agenda can be comprehended within the framework of nonlinear dynamics has gained ground in recent years (Dumas et al., 2015).

Indeed, many topical issues appear in the public spotlight "suddenly" and sometimes look quite strange. Surges in the activity of SOC communities can possibly explain the large-scale deviations of the online agenda from the mainstream media.

This study aimed to shed light on the composition and structure of the politicized segment of VK, a social network, in a broad chronological framework. We also hope that it contributes to answering questions about the role of online SOC communities in initiating protest movements and the impact of SOC network effects (in particular, data avalanches) on setting and changing the online political agenda.

Design and Tools

Cluster one was mapped in May 2021. Cluster two followed in May 2024. In both cases, we used an algorithm that functioned in a similar way to unwinding a ball of yarn. The "unwinding-a-ball-of-yarn" algorithm is a modification of the snowball method, which is well known in sociology and is used for sampling in conditions where research objects are difficult to access. However, despite their apparent similarity, the "unwinding" algorithm is not identical to the snowball algorithm. Firstly, unlike the snowball algorithm, which is intended for sampling, the "unwinding" algorithm aims to discover the main structure of the network cluster (all the most influential nodes and the connections between them, as well as some of the peripheral nodes). Secondly, the reflexivity connections that the "unwinding" algorithm tracks are fundamentally important for network analysis in themselves, given they elucidate essential network interactions. In contrast, the snowball algorithm uses connections (sometimes absolutely insignificant) between respondents only to find new respondents.

Mapping was conducted in two iterations, starting with a small number of communities that were selected as entry points to the network. Entry points were highlighted as sources of the most popular protest posts at the time of mapping. During the first iteration, related communities were identified for each entry point, and politicized communities were singled out from all the related communities. In this study, a certain significant number of commonly shared members was adopted as proof of the connection between communities. The vk.barkov.net service (module "Search for similar communities/shared audience") enabled finding of communities that included members of the original community. Common members are a channel of reflexivity through which communities can exchange their opinions, views, and calls to action. This channel can possibly act in both directions, therefore, for a formal analysis, we needed to represent one channel of reflexivity as two connections: incoming and outgoing. The weight of each connection (edge) was equal to the share (%) of common members in the original recipient community. Insignificant connections—with a weight of less than 1%—were removed from all calculations. In the second iteration, the communities that had been discovered in the first iteration played the role of the original communities.

Given the connections between nodes represent overlapping audiences, "unwinding a ball of yarn" allows us to detect, with the greatest probability, the nodes that are most attractive to online users. These are the communities with the strongest online presence: users strive to participate in them and view and repost their content. It is precisely these communities that are most likely to appear in the search results of the vk.barkov.net service, as they have many users in common with the original nodes. The "unwinding a ball of yarn" helps researchers quickly identify communities that are significant for the audience under study. In addition, the "unwinding-a ball-of-yarn" algorithm recorded many insignificant peripheral communities. Therefore, the population in question is not just a sample, but a general structure (of course, not fully detailed) of the segment of the Internet supporting oppositional discourse at certain points in time.

The mapping results were compiled into a node table and an edge table and visualized as a graph using Gephi software[3]. Through qualitative data coding, each node was assigned a categorical attribute indicating that it belonged to a particular political conglomerate. In this case, labels are categorical (nominal) descriptors: "liberals," "communists," "nationalists," etc. Use of such labels allowed us to provide

[3] https://gephi.org

a uniform description and obtain quantitative parameters of network clusters consisting of hundreds of nodes quickly and with affordable labor costs. It should be noted that labels (names of politicized online conglomerates) are simply conventional markings introduced by us to mark relatively homogeneous clusters. This study does not discuss whether conglomerates have or do not have connections (organizational, intellectual, etc.) with a particular political power or theoretical sociopolitical doctrine. Moreover, it is obvious that conglomerates are internally heterogeneous. They are composed of more or less dense clusters, i.e., factions. Labels, therefore, serve to organize the initial level by indicating the most noticeable differences between nodes. However, the system of labels does not claim to fully express the ideological struggle on the Internet.

Politicized communities show interest in political issues that encompass the past, present, and future of public policy and political system. Such communities discuss with some regularity certain questions that serve as markers for this study. Is the current public policy correct? If it should be changed, how? Should the current political system be dismantled? If yes, then why, how, and what new system should replace it? What events in the historical past justify the legitimacy of the current political system and its public policy, or, on the contrary, indicate their inadequacy? Labels only indicate fundamental differences in the answers to these questions.

The political agenda and the historical context strongly influenced the composition of the clusters in the first iteration. In the second iteration, the mapping algorithm identified the communities that were most attractive to the opposition audience, regardless of the ideological coloring of the entry points. This was significant because it is common for politically opposed communities to be connected to each other through eclectic conglomerates.

Cluster one contained mainly communities that strongly responded to and supported the street protests in the winter–spring of 2021. This subperiod included the events preceding and following the return to Russia and arrest of Alexei Navalny[4], a politician in the opposition, in 2021 (Troianovski & Nechepurenko, 2021). Liberal communities dominated in the first iteration of cluster one.

Cluster two reflected the response of opposition netizens to the course of the SMO. This time, in the first iteration, it was not only liberals who played a prominent role, but nationalists, who, as opposed to liberals, criticized the government for “unnecessary restriction” on the use of armaments.

Although the mapped clusters did not reflect the online opposition in its entirety, they had three properties that made it possible to extrapolate the results obtained through the study of these clusters to the broad online opposition. First, the clusters included communities with the deepest involvement in the alternative agenda and the protest discourse during the subperiods studied. Second, the “unwinding a ball of yarn” algorithm quickly led us to the communities that had the strongest appeal for the opposition audience. Thus, the basic structure of online opposition was determined.

[4] Alexey Navalny was added to the Register of Organizations and Individuals With Information on Their Involvement in Extremist Activities or Terrorism. Алексей Навальный был внесен в Перечень организаций и физических лиц, в отношении которых имеются сведения об их причастности к экстремистской деятельности или терроризму. https://www.fedsfm.ru/documents/terr-list

Third, the algorithm selectively identified the network periphery—small communities associated with large network hubs.

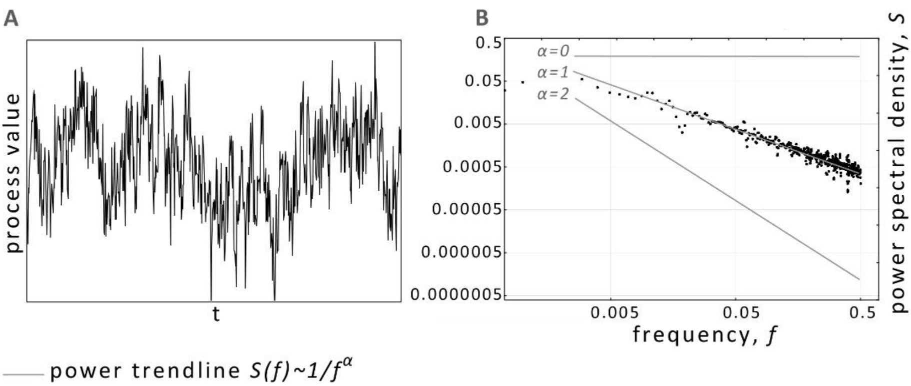
Using the Popsters service[5], we obtained time series for all the nodes in two clusters. These time series indicated the reposting activity of the communities, that is, the number of daily reposts, over two subperiods: from January 10, 2021 to April 30, 2021 for cluster one and from March 1, 2024 to May 31, 2024 for cluster two. This raw data is available on the website of the Center for Fractal Modeling[6].

The time series were subjected to spectral analysis in Statsoft Statistica (Fourier analysis module).

We identified a power law distribution or its absence in the spectrogram of each such series. Figure 4 shows a sample spectrogram of ideal artificial pink noise. If the power law exponent α was within the range of pink noise (between 0.5 and 1.5), this indicated that the community was mobilized. R^2 was the accuracy of the approximation of spectrogram points by a power law, which was calculated for each value of α.

Figure 4

Sample (A) and Spectrogram (B) of Pink Noise



Note. Source: Zhukov & Lyamin, 2017.

Results

The 2021 opposition cluster was the result of selecting related politicized communities from more than 7,000 communities that appeared in the search results of vk.barkov.net (Figure 5). The cluster included 168 liberal communities, 23 left and Stalinist, and eight nationalist communities, as well as 27 communities from the junk information conglomerate and 33 communities from the Doomscrollers conglomerate.

While doomscrolling communities on social media typically lack a coherent system of political ideas, it would be erroneous to label them as apolitical. These communities disseminate specific political sentiments and attitudes. They operate through a distinct interpretive lens that shapes their perception of the nation and its

[5] https://popsters.ru

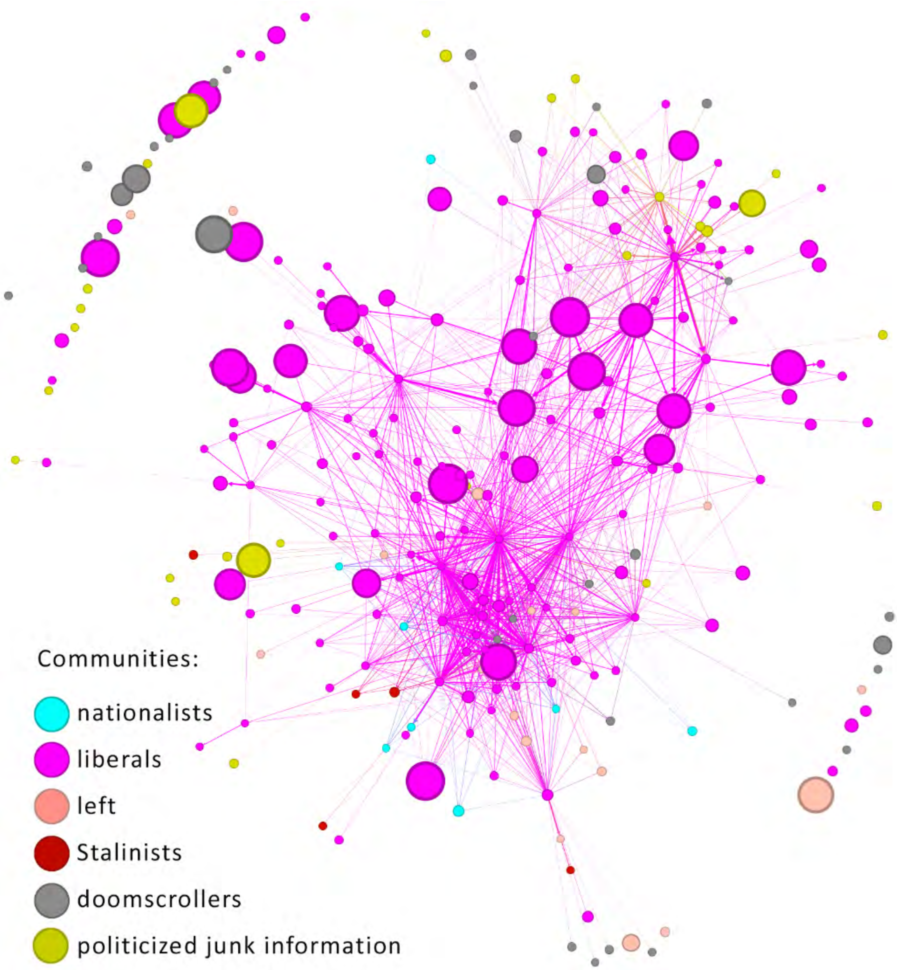
[6] http://ineternum.ru/2021-2024/

political landscape. Doomscrolling content tends to focus on news stories depicting "the ugliness of Russian life," ranging from historical narratives to mundane, everyday incidents. This framing cultivates a pervasive sense of national inferiority. Within these communities, strong negativity is consistently expressed toward both the government and the broader population.

The mapping results (a node table and an edge table in Gephi format) and mobilization indices for all nodes were posted on the website of the Center for Fractal Modeling.

Figure 5

Opposition Communities on VK as of May 2021



Note. Node diameter is proportional to the mobilization index. ForceAtlas2 layout settings: LinLog off; edge weight influence = 1.0.

The ForceAtlas2 algorithm was used to create the graph in Figure 5. This algorithm is based on a physical model: nodes are likened to objects that, being equally electrically charged, repel each other. Simultaneously, the edges connecting these objects imitate springs that attract the connected objects with some force and, thus, counteract the repulsion and divergence of the graph. Therefore, the visual density of the nodes corresponded to the density of their connections, which made it possible to interpret the structure (Jacomy et al., 2014).

The force of attraction of the spring depends on the number and weight of connections between nodes. Therefore, nodes that are more connected tend to cluster together, while pushing away less connected nodes and clusters. The developers of the algorithm ForceAtlas2 describe its heuristic capabilities as follows:

> The force-directed drawing has the specificity of placing each node depending on the other nodes. This process depends only on the connections between nodes. Eventual attributes of nodes are never taken into account … the technique has the advantage of allowing a visual interpretation of the structure. Its very essence is to turn structural proximities into visual proximities, facilitating the analysis and in particular the analysis of social networks. Noack (Noack, 2009) has shown that the proximities express communities. Noack relies on the very intuitive approach of Newman (Newman, 2006): actors have more relations inside their community than outside, communities are groups with denser relations. (Jacomy et al., 2014)

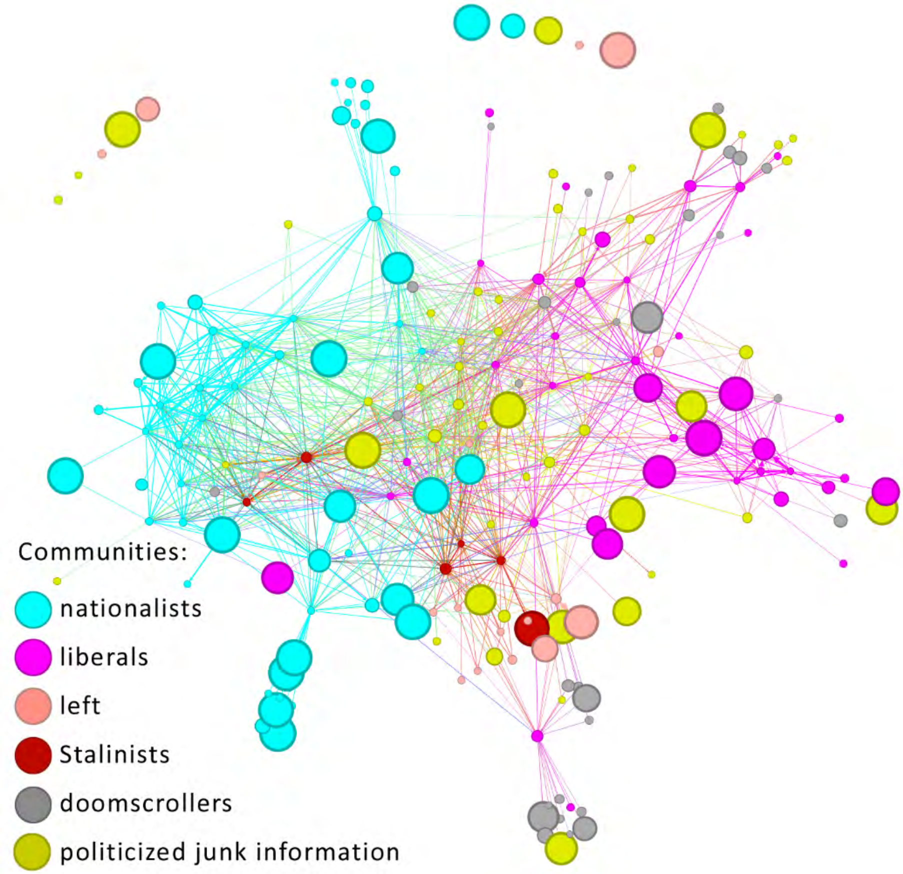
Thus, the visual density of nodes corresponds to the density of their connections, which made it possible to interpret the structure. We could view a kind of landscape of narratives of the opposition segment of the Net at certain moments. The algorithm ForceAtlas2 visualized clusters of ideologically related communities, the ideological distance between different factions, and their mutual arrangement. For example, Figure 6 depicts that liberal communities are mixed with communities from the conglomerates Doomscrollers and Junk Information.

As noted previously, due to the political context, this cluster was dominated by liberal communities that attempted to instigate a series of mass street protests in the spring of 2021, using the arrest of Alexei Navalny[7] as a pretext. We considered 34 communities with $\alpha > .5$ as likely mobilized. Of the mobilized communities, the absolute majority belonged to the liberal conglomerate (29 nodes; 17% of the liberal sector). One left community, two communities from the Junk Information and two communities from Doomscrollers conglomerates were also mobilized.

Only 13 nodes had $\alpha > .7$ with $R^2 > .5$, which positively indicated the presence of pink noise. This number may seem small, but the literature does not mention what number should be regarded as large or small in this context, that is, sufficient enough or not to spark protests. At the least, the presence of several simultaneously

[7] Alexey Navalny was added to the Register of Organizations and Individuals with Information on Their Involvement in Extremist Activities or Terrorism. Алексей Навальный был внесен в Перечень организаций и физических лиц, в отношении которых имеются сведения об их причастности к экстремистской деятельности или терроризму. https://www.fedsfm.ru/documents/terr-list

Figure 6
Opposition Communities on VK as of May 2024



Note. Node diameter is proportional to the mobilization index. ForceAtlas2 layout settings: LinLog off; edge weight influence = 1.0.

mobilized—and, moreover, connected—communities indicated a certain number of people among the opposition who were willing to act. Those individuals' activity could trigger self-sustaining protests. Our study showed that mobilized communities had strong ties to each other and numerous connections with the periphery. They could therefore claim the role of generators of an alternative agenda for online opposition.

Three years later, the liberal protest core on the VK ceased to exist (Table 1). Of the communities mobilized in 2021, 70.6% were removed by prosecutors and courts; the figure for the category "non-mobilized in 2021" was 27.6%.

Table 1
Node Status of the 2021 Opposition Cluster on VK as of March 2024

Status	Share among mobilized communities (%)	Share among non-mobilized communities (%)
Removed at the request of prosecutors or by court order	70.6	27.6
No longer active (but still exists)	8.8	18.2
Changed topic	0.0	16.0
Page removed	0.0	5.8
Still active	20.6	32.4

The 2024 opposition cluster is shown in Figure 5. It consisted of 200 communities (Table 2). More than 10,000 groups were sifted to map this cluster.

Table 2
Mobilization of the 2024 Opposition Cluster on VK From March 1, 2024 to May 31, 2024

Conglomerate	Number of communities (units)	Mobilized communities (units)	Share of mobilized communities (%)
Nationalists	56	15	26.8
Politicized junk information	51	10	19.6
Left and Stalinists	24	3	12.5
Liberals	39	4	10.3
Doomscrollers	30	2	6.7

Three years later, the 2021 liberal cluster that was almost completely eliminated had regenerated. Figure 6 shows a significant liberal infrastructure comprised not only new communities, but mainly second-rank communities that came to the fore. Although online communities that could support the liberal discourse still existed, they were no longer determining the agenda in the opposition segment of the network. Liberal communities were the least mobilized compared to their rivals.

Mapping active online opposition showed that nationalists had been flourishing, with numerous communities. Nationalist communities comprised slightly less than half of the 34 mobilized communities we found (Table 2).

It should be noted that there was disunity among nationalist communities. These communities were gathered in several clusters, which probably indicates certain ideological differences among them. The left communities were very modestly represented in both cluster one and two. One of the traditional explanations for the poor representation of the left online is that they rely on older supporters who prefer real life to Internet use.

Discussion

The results show that the emergence of pink noise in a certain segment of the VK, i.e., the mobilization of multiple protest communities of a certain political orientation, occurs against the background of a change in the central topics of the opposition discourse (alternative online political agenda). Moreover, in the first instance, pink noise accompanied not only online mobilization, but street protests. These observations support the hypotheses that the emergence of multiple mobilized communities can both provoke street protests and focus the attention of netizens on topics that interest mobilized communities. At the same time, the presented facts are not sufficient to exhaustively confirm these hypotheses.

However, it is apparent that SOC effects are characteristic of online communities and, moreover, allow us to diagnose the state of these communities. SOC communities are distinguished by a high level of engagement among their members, which separates them from many artificially "inflated" online communities. Members of highly engaged mobilized communities are connected to each other by reflexivity relations. The essence of such relations is that members tend to share information, disseminate it, and change their behavior under its influence. Such characteristics ensure the integrity of the community as a system and its tendency to react strongly to weak stimuli.

As this study, along with a number of other works mentioned, has shown, self-organized critical states existing on the Internet can be confidently identified. This means that the corresponding processes can be monitored using the latest methods: tracking avalanche-prone objects, avalanche-prone periods, and sources and channels of avalanche propagation.

We believe that SOC theory provides researchers with a toolkit for monitoring political mobilization in social media. This toolkit has a number of advantages. Firstly, it has a sound theoretical basis: the description of SOC systems within SOC theory coincides with the characteristics of highly engaged mobilized communities. Secondly, the proposed toolkit is very economical in terms of the initial data required. The analysis of one time series allows for the finding of important properties of a community. Thirdly, the toolkit makes it possible to measure intersubjective phenomena that are usually elusive: engagement, involvement, and mobilization.

Conclusions

Neither the 2021 nor the 2024 cluster fully captures the spectrum of online opposition. Instead, they reflect the segment that was most active during the period under review and exerted the greatest influence on oppositional discourse at the time.

The 2021 opposition cluster was mainly composed of liberal communities, many of which, being mobilized, could lay claim to the role of architects of the alternative online agenda. After the decline of street protests (in mid-2021) and at the beginning of the SMO, the core of this cluster was eliminated by courts and prosecutors. Furthermore, it was mostly mobilized communities that were removed.

The cluster mapped in May 2024, however, included numerous liberal communities. Although liberal communities survived, they were no longer mobilized. This observation probably indicates that their ideas and calls no longer inspired trust and a feeling of involvement in opposition-minded netizens.

The 2024 opposition cluster could be called predominantly nationalist. Russian nationalists were part of many mobilized communities and, therefore, demonstrated a willingness to act. The SMO led to a change in ideas shaping the opposition discourse online, whereby the initiative passed from liberals to nationalists.

Nationalists were focused on winning the SMO, intensifying military operations, and "eradicating internal enemies," including pro-Western liberals and migrants. While maintaining a critical attitude towards the Kremlin's political course, nationalists supported the government, inasmuch as the government aimed to achieve the Russian goals of the SMO.

Data Availability Statement

The raw data, mapping results, and mobilization indices for all nodes were posted on the website of the Center for Fractal Modeling: http://ineternum.ru/2021-2024/

References

Açıkalın, Ş. N., & Artun, E. C. (2019). The concept of self-organized criticality: The case study of the Arab Uprising. In Ş. Ş. Erçetin & N. Potas (Eds.), *Chaos, complexity and leadership 2017: Explorations of chaos and complexity theory* (pp. 73–85). Springer. https://doi.org/10.1007/978-3-319-89875-9_7

Aguilera, M., Morer, I., Barandiaran, X., & Bedia, M. (2013). Quantifying political self-organization in social media: Fractal patterns in the Spanish 15M movement on Twitter[8]. In *ECAL 2013: The Twelfth European Conference on Artificial Life* (pp. 395–402). MIT Press. https://doi.org/10.7551/978-0-262-31709-2-ch057

Arnold, J., Bond, K., Chenoweth, E., & Pressman, J. (2018, May 31). These are the four largest protests since Trump was inaugurated. *The Washington Post*. https://www.washingtonpost.com/news/monkey-cage/wp/2018/05/31/these-are-the-four-largest-protests-since-trump-was-inaugurated

Bak, P. (1996). *How nature works: The science of self-organized criticality*. Copernicus. https://doi.org/10.1007/978-1-4757-5426-1

Bak, P., Tang, C., & Wiesenfeld, K. (1988). Self-organized criticality. *Physical Review A*, *38*(1), 364–374. https://doi.org/10.1103/PhysRevA.38.364

Banerjee, S., Biswas, S., Chakrabarti, B. K., Challagundla, S. K., Ghosh, A., Guntaka, S. R., Koganti, H., Kondapalli, A. R., Maiti, R., Mitra, M., & Ram, D. R. S.

[8] Twitter® is a trademark of Twitter Inc., registered in the U.S. and other countries. По решению Роскомнадзора, социальная сеть Twitter полностью заблокирована в России как организация, занимающаяся распространением запрещенного контента.

(2023). Evolutionary dynamics of social inequality and coincidence of Gini and Kolkata indices under unrestricted competition. *International Journal of Modern Physics C*, *34*(4), Article 2350048. https://doi.org/10.1142/S0129183123500481

Banerjee, S., Biswas, S., Chakrabarti, B. K., Ghosh, A., & Mitra, M. (2023). Sandpile universality in social inequality: Gini and Kolkata measures. *Entropy*, *25*(5), Article 735. https://doi.org/10.3390/e25050735

Borodkin, L. I. (2019). Vyzovy nestabil'nosti: Kontseptsii sinergetiki v izuchenii istoricheskogo razvitiia Rossii [Challenges of instability: The concepts of synergetics in studying the historical development of Russia]. *Ural Historical Journal*, 2, 127–136. http://www.doi.org/10.30759/1728-9718-2019-2(63)-127-136

Brichoux, D., & Johnson, P. E. (2002). The power of commitment in cooperative social action. *Journal of Artificial Societies and Social Simulation*, *5*(3).

Brunk, G. G. (2001). Self-organized criticality: A new theory of political behaviour and some of its implications. *British Journal of Political Science*, *31*(2), 427–445. https://doi.org/10.1017/S0007123401000163

Dmitriev, A., & Dmitriev, V. (2021). Identification of self-organized critical state on Twitter[9] based on the retweets' time series analysis. *Complexity*, *2021*, Article 6612785. https://doi.org/10.1155/2021/6612785

Dmitriev, A., Lebedev, A., Kornilov, V., & Dmitriev, V. (2023). Twitter[9] self-organization to the edge of a phase transition: Discrete-time model and effective early warning signals in phase space. *Complexity*, *2023*, Article 3315750. https://doi.org/10.1155/2023/3315750

Dumas, C. L., LaManna, D., Harrison, T. M., Ravi, S., Kotfila, C., Gervais, N., Hagen, L., & Chen, F. (2015). Examining political mobilization of online communities through e-petitioning behavior in We the People. *Big Data & Society*, *2*(2). https://doi.org/10.1177/2053951715598170

Epstein, J. M. (2002). Modeling civil violence: An agent-based computational approach. *Proceedings of the National Academy of Sciences*, *99*(Suppl. 3), 7243–7250. https://doi.org/10.1073/pnas.092080199

Golovashina, O. V. (2017). Samoorganizovannaia kritichnost' aktorno-setevoi teorii [Self-organized criticality of the actor-network theory]. *Philosophy and Culture, 7*, 23–31. https://doi.org/10.7256/2454-0757.2017.7.21658

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLOS ONE*, *9*(6), Article e98679. https://doi.org/10.1371/journal.pone.0098679

[9] Twitter® is a trademark of Twitter Inc., registered in the U.S. and other countries. По решению Роскомнадзора, социальная сеть Twitter полностью заблокирована в России как организация, занимающаяся распространением запрещенного контента.

Kapitsa, S. P., Kurdyumov, S. P., & Malinetskii, G. G. (2001). *Sinergetika i prognozy budushchego* [Synergetics and forecasts of the future]. URSS.

Kron, T., & Grund, T. (2009). Society as a self-organized critical system. *Cybernetics & Human Knowing*, *16*(1–2), 65–82.

Latonov, V. V., & Latonova, A. V. (2022). Primenenie teorii samoorganizovannoi kritichnosti k analizu liberal'noi povestki v presse 1815–1825 gg [Application of the theory of self-organized criticality to the analysis of the liberal agenda in the press of 1815–1825]. *Historical Informatics*, *3*, 156–165. https://doi.org/10.7256/2585-7797.2022.3.38752

Le Goff, C. (2020, February 27). *Yellow vests, rising violence—what's happening in France?* World Economic Forum. https://www.weforum.org/stories/2020/02/france-protests-yellow-vests-today

Lu, P., Yang, H., Li, M., & Zhang, Z. (2021). The sandpile model and empire dynamics. *Chaos, Solitons & Fractals*, 143, Article 110615. http://www.doi.org/10.1016/j.chaos.2020.110615

Makowsky, M. D., & Rubin, J. (2013). An agent-based model of centralized institutions, social network technology, and revolution. *PLOS ONE*, *8*(11), Article e80380. https://doi.org/10.1371/journal.pone.0080380

Malinetskii, G. G. (2013). Chudo samoorganizovannoi kritichnosti [The miracle of self-organized criticality] [Foreword]. In P. Bak, *Kak rabotaet priroda: Teoriia samoorganizovannoi kritichnosti* [How nature works: The science of self-organized criticality] (V. E. Podobed, A. V. Kondrat'ev, & O. L. Shevchuk, Trans.) (pp. 13–46). URSS.

Maulana, A., & Situngkir, H. (2010). *Power laws in elections—A survey*. SSRN. https://doi.org/10.2139/ssrn.1660603

Picoli, S., del Castillo-Mussot, M., Ribeiro, H. V., Lenzi, E. K., & Mendes, R. S. (2014). Universal bursty behaviour in human violent conflicts. *Scientific Reports*, *4*, Article 4773. https://doi.org/10.1038/srep04773

Podlazov, A. V. (2001). *Novye matematicheskie modeli, metody i kharakteristiki v teorii samoorganizovannoi kritichnostii* [New mathematical models, methods and characteristics in the theory of self-organized criticality] (Unpublished doctoral dissertation). Keldysh Institute of Applied Mathematics of Russian Academy of Sciences.

Roberts, D. C., & Turcotte, D. L. (1998). Fractality and self-organized criticality of wars. *Fractals*, *6*(4), 351–357. https://doi.org/10.1142/S0218348X98000407

Schulte, F., & Trinn, C. (2024). Collective emotions, triggering events, and self-organization: The forest-fire model of cultural identity conflict escalation. *Aggression and Violent Behavior*, *78*, Article 101954. https://doi.org/10.1016/j.avb.2024.101954

Shimada, I., & Koyama, T. (2015). A theory for complex system's social change: An application of a general "criticality" model. *Interdisciplinary Description of Complex Systems*, *13*(3), 342–353. https://doi.org/10.7906/indecs.13.3.1

Tadić, B., Dankulov, M. M., & Melnik, R. (2017). Mechanisms of self-organized criticality in social processes of knowledge creation. *Physical Review E*, *96*(3), Article 32307. https://doi.org/10.1103/PhysRevE.96.032307

Tadić, B., Dankulov, M. M., & Melnik, R. (2023). Evolving cycles and self-organised criticality in social dynamics. *Chaos, Solitons & Fractals*, *171*, Article 113459. https://doi.org/10.1016/j.chaos.2023.113459

Tadić, B., & Melnik, R. (2021). Self-organised critical dynamics as a key to fundamental features of complexity in physical, biological, and social networks. *Dynamics*, *1*(2), 181–197. https://doi.org/10.3390/dynamics1020011

Thietart, R.-A. (2016). Strategy dynamics: Agency, path dependency, and self-organized emergence. *Strategic Management Journal*, *37*(4), 774–792. https://doi.org/10.1002/smj.2368

Trinn, C. (2018). Criticality, entropy and conflict. *Systems Research and Behavioral Science*, *35*(6), 746–758. https://doi.org/10.1002/sres.2516

Trinn, C., & Naumann, L. (2023). Guns and lightning: Power law distributions in intrastate conflict intensity dynamics. *Conflict Management and Peace Science*, *40*(4), 373–397. https://doi.org/10.1177/07388942221092126

Troianovski, A., & Nechepurenko, I. (2021, August 25). Navalny[10] arrested on return to Moscow in battle of wills with Putin. *The New York Times*. https://www.nytimes.com/2021/01/17/world/europe/navalny-russia-return.html

Zhukov, D. (2022). How the theory of self-organized criticality explains punctuated equilibrium in social systems. *Methodological Innovations*, *15*(2), 163–177. https://doi.org/10.1177/20597991221100427

Zhukov, D. S., & Lyamin, S. K. (2017). Revoliutsii v Seti: Prilozhenie teorii samoorganizovannoi kritichnosti k izucheniiu protestnykh dvizhenii [Revolution in the Internet: Self-organized criticality theory to study protest movements]. *Historical Informatics*, *4*, 11–43. https://doi.org/10.7256/2585-7797.2017.4.24559

[10] Alexey Navalny was added to the Register of Organizations and Individuals with Information on Their Involvement in Extremist Activities or Terrorism. Алексей Навальный был внесен в Перечень организаций и физических лиц, в отношении которых имеются сведения об их причастности к экстремистской деятельности или терроризму. https://www.fedsfm.ru/documents/terr-list