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MODELS OF JOINT DYNAMICS OF OPINIONS AND ACTIONS IN ONLINE SOCIAL NETWORKS. PART I: Primary Data Analysis[1]

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Abstract. Based on *VKontakte* data, we study the influence of various factors on the dynamics of opinions and actions both at the macro level ("public opinion") and at the micro level (the opinions and actions of individual agents). Primary analysis results are presented for the dynamics of opinions and actions of agents in this social network. In particular, the growing polarization of opinions at the macro level is detected; changes in the opinions of agents over time are observed; socio-demographic characteristics of agents who changed their opinions are determined; a good consistency between the opinions and actions of agents is revealed; finally, an explicit relationship between the opinions and actions of agents is established.

Keywords: social network, agent, opinion, action, social influence, cognitive dissonance, trust in information.

INTRODUCTION

Since the 1950s, researchers have been developing mathematical models of opinion dynamics to explain changes in the beliefs of individuals (*agents*) under the influence of socio-psychological factors; for example, we refer to the publications [1–12] on the subject. In parallel, the same effects have been studied in social psychology; see [13–15], etc.

These investigations are still topical today, particularly due to the rapid development of online social media, where information processes significantly influence the political, economic, and social life of society. For example, under uncertainty and no knowledge, the inaccurate information about the measures to combat the COVID-19 pandemic, which was once disseminated by reputable but often incompetent social networkers, caused a destructive information agenda and undermined the effectiveness of pandemic control efforts through changing the beliefs of network users [16]. At the same time, mathematical models of opinion and action dynamics can be used to predict changes in public beliefs and develop necessary strategies to protect public health. However, the identification of such models is a complex interdisciplinary task.

In this paper, the basic model is the mathematical model of the joint dynamics of opinions and actions of the agents proposed in [17]. As an "empirical base" we adopt the posts, comments, and likes in *VKontakte*, a popular online social network, on wearing medical masks that appeared from March 2020 to February 2021 inclusive. *An opinion* is conventionally interpreted as the "tone" of an agent's comment, as assessed by an automatic classifier; *an action* is conventionally[2]

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[2] Of course, commenting and liking are inherently actions. (Within the actional approach [1, 3], different types of actions and relations between them underlie modeling and the analysis of information processes in a network.) Therefore, the separation of opinions (comments) and actions (likes) has an obvious alternative, i.e., the introduction of hidden variables (opinions) and their identification by observable "actions" (comments and likes) within hidden Markov models, Bayesian networks, etc. Such approaches seem promising and the corresponding models will be considered in part III of the study.

interpreted as the tone of a comment with an agent's like.

This multi-part study attempts to answer the following questions:

1) How consistent are the opinions and actions of agents with each other?

2) Do agents change their opinions and actions over time?

3) Who are these (opinion- and action-changing) agents? Do they differ from others in their socio-demographic characteristics?

4) Which models better describe the dynamics of the opinions and actions of agents (linear, threshold, etc.)?

5) Are the influence of actions on opinions (*cognitive dissonance*) and the converse effect significant?

6) Under which factors do the opinions and actions of agents change? Among such factors, we consider:

- the agent's previous opinions or (and) actions;
- social influence:
  – *public opinion* (the averaged shares of certain opinions and actions of the entire social network, i.e., the so-called *macro model*, where the network is conventionally treated as one agent);
  – the opinions or (and) actions of the agent's environment (the agents with the friendship relation to a given agent), i.e., the averaged and (or) individual ones (the so-called *micro model*);
- some unobservable (*latent*) characteristics of the agent.

7) Does an agent's change in the opinion (action) depend on his trust in the source of information? Does it depend on the content of that information?

Question no. 6 has the highest complexity: to answer, we need to analyze all combinations of explanatory variables and order the models with a fixed number of variables by the maximum reduction of the prediction error of the explained variable.

In part I, we examine the dynamics of real opinions and actions of agents concerning their attitude toward wearing medical masks in *VKontakte* as an example. The remainder of this paper is organized as follows. Section 1 describes the initial data. In Section 2, we propose an approach to identifying agents' opinions in the network based on deep learning methods. Section 3 characterizes the dynamics of opinions and actions at the macro level (how much support individual users and the entire online community have for wearing medical masks, how much public opinion changes over time, etc.) as well as the features of information interaction between agents. Finally, the resulting relationship between the opinions and actions of social network agents is presented and analyzed in Section 4. Thus, the paper provides answers to Questions nos. 1–3. Parts II and III of the study will deal with the identification of macro and micro models of the joint dynamics of opinions and actions to answer Questions nos. 4–7.

1. ANALYSIS OF NETWORK INTERACTIONS: INITIAL DATA AND KEY FACTORS

The objects of the media landscape under consideration are information sources and users of *VKontakte*. Information sources publish news covering various aspects of the COVID-19 pandemic and influence network users. Network users (hereinafter referred to as "agents") respond to the messages of information sources and perform actions in the network according to their interests and opinions (comment and like), interacting with each other.

The data were collected for the information sources selected by experts based on the Medialogy's rating; see https://www.mlg.ru/. All sources have *VKontakte* pages and publish news on topics of public importance: *RIA Novosti* (2.9 million subscribers), *RT News* (1.3 million subscribers), *Komsomol'skaya Pravda* (1.1 million subscribers), *RBC* (0.9 million subscribers), *TSARGRAD TV* (0.7 million subscribers), *Moscow 24* (0.5 million subscribers), *Yekaterinburg News E1RU* (0.3 million subscribers), *Snob* (0.3 million subscribers), *Fontanka.ru* (0.3 million subscribers), *Gazeta.ru* (0.2 million subscribers), and *Interfax* (0.1 million subscribers).

We considered and analyzed the posts of these sources on COVID-19 (over 60 thousand posts) and the network response to them for the period from March 1, 2020, to March 1, 2021, (over 2 million comments to the posts and over 7 million likes to the posts and comments). A detailed description of the data collection approach can be found in the papers [18, 19], including some analysis results of network user activity.[3] Then the comments and likes directly related to wearing medical masks were identified.

In view of the initial data, we formalize the descriptive factors of the online social network needed to analyze and identify the models of the joint dynamics of opinions and actions. According to [1, 3], let the network participants be *agents* from a set $N = \{1, 2, ..., n\}$. They commit some *acts*[4] from a fixed set

[3] The data were collected within project 20-04-60296 supported by the Russian Foundation for Basic Research. We are grateful to E.V. Belyavskii and I.V. Kozitsin for their data collection efforts.

[4] The term "action" used in [3] is replaced here by "act" to avoid confusion with actions in models of the joint dynamics of opinions and actions.

$K = \{1, 2, ..., k\}$ at certain time instants t of an interval T. Our considerations are restricted to the following types of acts ($K = \{1, 2\}$):

– publishing a comment on a post or another comment,

– liking a comment.

We denote by Δ the set of acts.[5] Each act $a \in \Delta$ is described by three parameters: the agent who committed it, the type of the act, and the time instant when it was committed. We introduce the following functions to characterize acts:

- f_a: $\Delta \rightarrow N$, associating with each act $a \in \Delta$ the agent $i \in N$ who committed it;
- f_t: $\Delta \rightarrow T$, associating with each act $a \in \Delta$ the time instant $t \in T$ when it was committed;
- f_k: $\Delta \rightarrow K$, associating with each act $a \in \Delta$ its type $j \in K$.

On the set of acts, we define a binary partial-order relation of the form "*a* causes *b*": $a \rightarrow b$. If $a \rightarrow b$, $a \neq b$, and there does not exist $c \in \Delta$ such that $a \rightarrow c$ and $c \rightarrow b$, then a is *the direct cause of* b: $a \downarrow b$. The binary relation $a \rightarrow b$ is supposed to hold in the following cases:

- a is a comment and b is a like to it.
- a is a comment and b is a comment on it.
- a and b coincide.

For each agent $i \in N$, we define the set of all his acts $\delta_i = \{a \in \Delta \mid f_a(a) = i\}$ and the set of his friends $N_i \subseteq N$. (The formal "friendship" relation in an online social network implies that an agent can receive information about the comments posted by his friends, the likes they give, etc.).

Opinions and actions. When modeling the joint dynamics of opinions and actions, we conventionally interpret the agent's *opinion* as his attitude to wearing medical masks, expressed in a comment.

The agent's opinion in a comment $b \in \Delta$ ($f_k(b) = 1$) is formally defined in three ways as follows:

- $r' \in \{0, 1, 2\}$, where the classification results 0, 1, and 2 correspond to "against masks" (or "–"), "for masks" (or "+"), and "neutral/irrelevant" (or "="). This result is determined using the stochastic vector $(p_-, p_+, p_=)$ calculated by the classifier. In machine learning, the components of such a vector are interpreted as the probabilities of the object's belonging to appropriate classes.
- $r'' = \dfrac{p_+}{p_+ + p_-} \in [0, 1]$, the confidence that the comment reflects the "for masks" opinion. Note that $r' = 0$ or $r' = 1$ for this comment.
- $r = \dfrac{p_+ - p_-}{p_+ + p_-} \in [-1, 1]$, where $r = 1$ and $r = -1$ indicate strong confidence in expressing the "for masks" opinion (the "against masks" opinion, respectively). Note that either $r' = 0$ or $r' = 1$ for this comment.

Let a like to some comment be *an action* as well; its assessment coincides with that of the corresponding comment liked: $y' \in \{0, 1, 2\}$, $y'' \in [0,1]$, and $y \in [-1,1]$. For example, for a like $a \in \Delta$, $y'(a) = r'(b)$, where b is the corresponding comment liked (i.e., $b \downarrow a$). To simplify further notations, we adopt the conventions $r'(a) = y'(a)$, $r''(a) = y''(a)$, and $r(a) = y(a)$. Assume that the instant of liking coincides with the instant of publishing the corresponding comment liked.

The agent's position is an aggregate characteristic of the agent that reflects his attitude to wearing medical masks. We consider only the position s_i of agent i for which there exists $a \in \delta_i$, $r'(a) \in \{0, 1\}$, such that

$$s_i = \begin{cases} 0, & \bar{r}_i \le 0.5 - \epsilon, \\ 1, & \bar{r}_i \ge 0.5 + \epsilon, \\ 2, & |\bar{r}_i - 0.5| < \epsilon, \end{cases}$$

where $\bar{r}_i = \dfrac{\sum_{a \in \delta_i \mid r'(a) \in \{0, 1\}} r'(a)}{|\{a \in \delta_i \mid r'(a) \in \{0, 1\}\}|} \in [0, 1]$ is the average of his opinions and the actions "for" and "against." In what follows, we choose $\epsilon = 0.05$.

2. IDENTIFICATION OF AGENTS' OPINIONS

The opinions of agents were determined based on their comments on COVID-19 posts containing the keywords "*mask*," "*muzzle*," and their derivatives (about 60 thousand comments).

Such comments were subjected to preliminary automatic text processing, particularly to remove references to the interlocutor and Internet addresses. Part of the collected sample (approximately 10 thousand comments) was labeled by experts: each comment was given an appropriate-class label reflecting the attitude to the masks: "0" ("against"), "1" ("for"), or "2"

[5] The set of relevant comments on wearing medical masks (see Section 2) and their likes.

(“neutral”). Here are labeled examples (the original spelling and punctuation are preserved): “*Well we see the stats and so keep wearing masks and all that stuff*” (for masks), “*I go without a mask. I am a COVID dissident*” (against masks), “*He speaks funnily about masks in Russia*” (neutral/irrelevant).

To solve the classification problem, we developed a neural network classifier based on the pre-trained BERT language model (Conversational RuBERT) [20]. In addition to the BERT layer, its architecture includes additional fully connected layers, dropout layers, and a softmax layer. Note the socio-psychological studies of social network users during the COVID-19 pandemic [21–24], which are close to this problem. However, first, we identified the opinions of network users instead of, e.g., emotions or hate speech and, second, solved the problem for a large target data sample.

The labeled sample was subjected to transformations. After its random shuffle, the training (90%), validation (5%), and test (5%) samples were formed. The classes were balanced using weights to compensate the volume of a certain opinion class: the more examples were contained in a class, the smaller weight the class examples had in the loss function minimized by training. Then we found the hyperparameters of the classifier with the maximum quality value on the validation sample under the resource constraints: 192 tokens as the maximum input sequence length, 16 examples as the size of the training packet, and 7 training epochs. As a result, *the quality value of the trained classifier (accuracy) on the test sample was 0.82.* (For each class, the value of the measure F_1 was not less than 0.7.) For comparison, the baseline classifier (the logistic regression) showed an accuracy of 0.6 on the test sample after finding the optimal values of hyperparameters on the validation sample.

The trained classifier was applied to the entire dataset of mask-relevant comments.

3. STUDY OF THE OPINIONS AND ACTIONS OF AGENTS

This section is organized as follows. Subsection 3.1 presents the characteristics of social network agents with a position on the masks (the socio-demographic characteristics of agents as well as the characteristics of their opinions and actions). Subsection 3.2 is devoted to the dynamics of opinions and actions *at the macro level* (the shares of agents with a certain opinion, without analyzing the opinions of individual agents) and the connection with exogenous factors and trends. Subsection 3.3 considers the structure of information interaction between agents in the network: the characteristics of this structure, the information interaction preferences of agents, and the existence of isolated information communities.

3.1 The characteristics of agents

This subsection considers agents with a position (i.e., $s_i \in \{0, 1, 2\}$ for agent *i*) who expressed at least one opinion. The classifier determined a total of 16 thousand such agents who expressed their opinions in 50 thousand comments (including 38 thousand “for” or “against” opinions).

For the entire period under examination, the share of agents with the “for” position was 56%; “against,” 37%; “neutral,” 7%. However, only half of the agents (8 thousand) provided information in social network profiles (i.e., their profiles were not closed or deleted). For these agents, the proportions slightly changed to wearing masks: 58% “for,” 35% “against,” and 7% “neutral.” *Socio-demographic indicators* (gender, age, country, and city) were analyzed for the agents with accessible profiles.

Gender and age of agents. The distribution of agents by gender is shown in Fig. 1. *Among the agents with the “against” position, there was a high share of males* (61%) *compared to the proportion of males among the agents with the “for” position* (51%).

Information about the day and month of birth was provided by 73% of the agents; the year of birth, by only 46% of the agents. The distribution of agents by age is shown in Fig. 2. (The age was defined as of March 1, 2020. The age category was determined based on the theory of generations [25]: the average life expectancy is 80 years, and it consists of four periods of about 20 years: childhood → youth → middle age → old age.)

For the agents with the “against” position, the share of older age groups was higher (19.2% in category 41–60 and 7.2% in category 60+) *than for the agents with the “for” position* (15.2% in category 41–60 and 6.9% in category 60+).

The geographical location of agents. The majority of agents were from Russia (79%), and Ukraine and Belarus completed the top three countries. (15% of agents did not specify the country.) Approximately the same distribution was observed for agents with a fixed position.

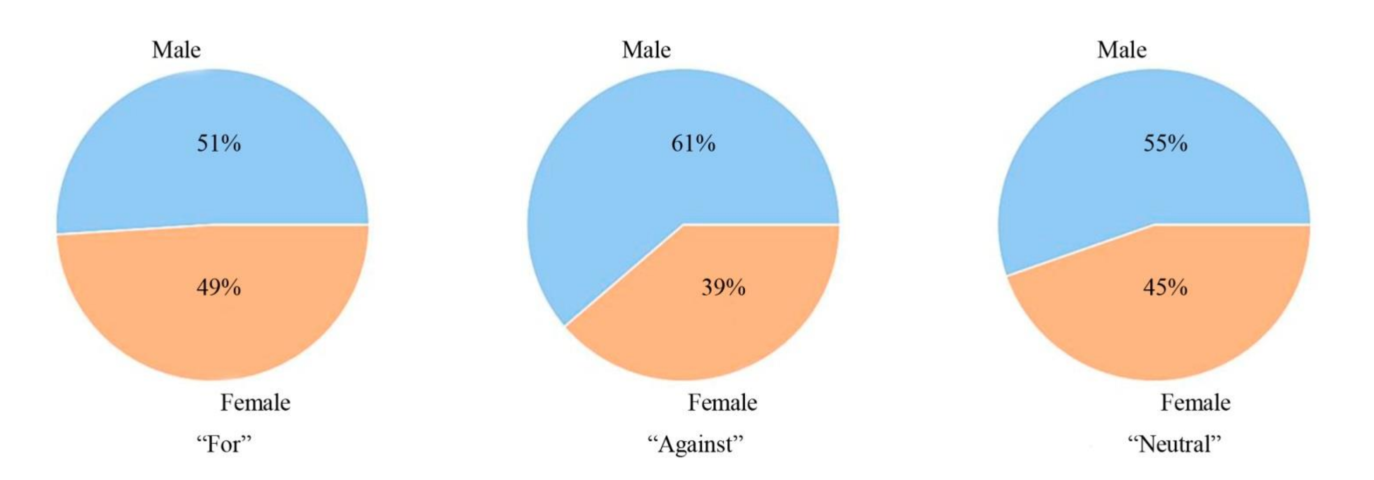

Fig. 1. The distribution of agents with a given position by gender.

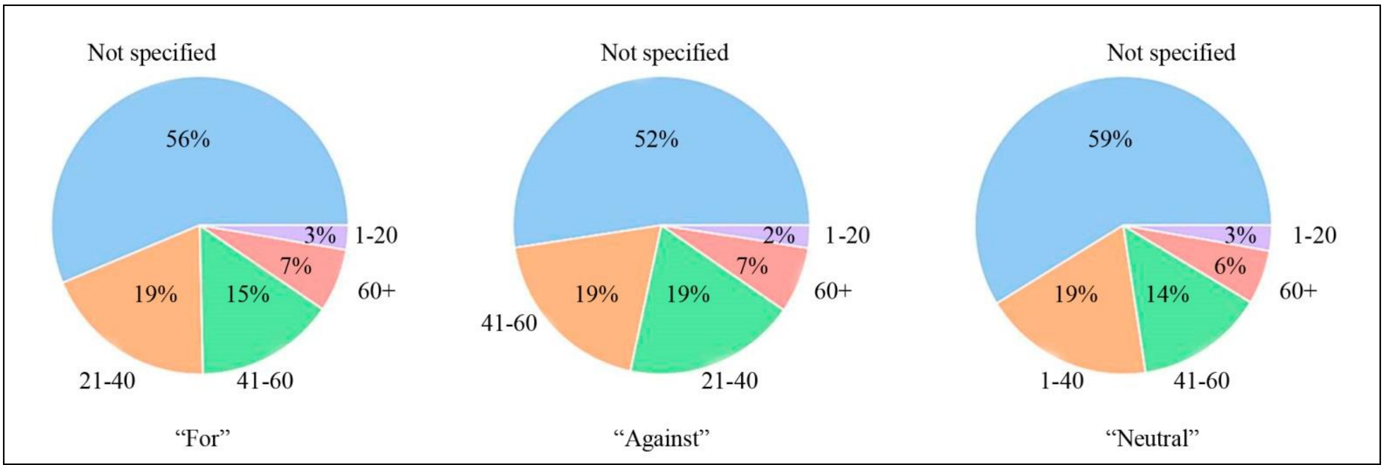

Fig. 2. The distribution of agents with a given position by age category.

The city of residence was specified for 75% of agents; see the distribution in Fig. 3.

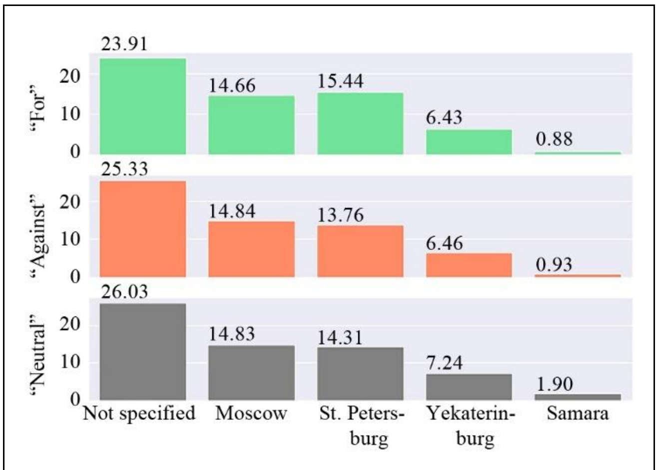

Fig. 3. The distribution of agents with a given position by city.

According to this figure, the first three cities are Moscow, St. Petersburg, and Yekaterinburg. *Among the agents with the "for" position, there were more residents of St. Petersburg; among those with the "against" position, there were more residents of Moscow.*

The opinions and actions of agents. From the study of socio-demographic characteristics, we proceed to the direct analysis of the opinions and actions of the agents with a position.

The distribution of agents by the number of "for" and "against" opinions is shown in Fig. 4. The sample contained *14.4 thousand agents* with a position. On average, an agent with the "for" or "against" opinion made 1.1 comments for wearing masks and 1.5 comments against them during the period under consideration. In other words, *the activity in expressing opinions was low*: *79% of agents commented "for" or "against" at most twice.*

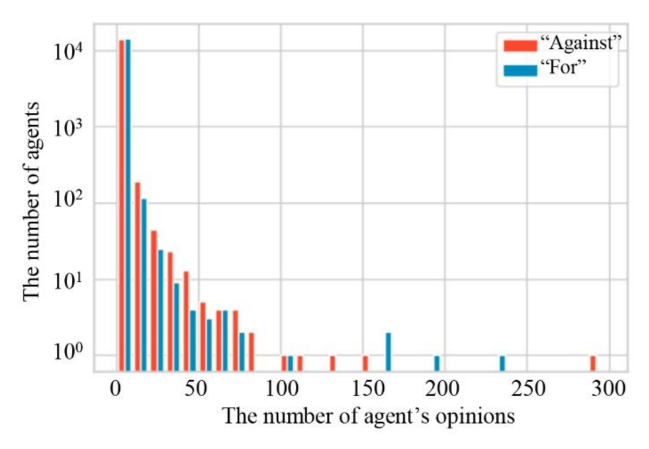

Fig. 4. The distribution of agents by the number of opinions expressed.

About 125 thousand likes (84.5 thousand “against” and 40.8 thousand “for”) were given to comments with the “for” or “against” opinion by *44 thousand agents*. (About a third of the likes were given by 6 thousand agents who expressed the “for” or “against” opinion in the comments.) On average, such an agent left 1.9 “against” likes and 0.9 “for” likes. Thus, *likers were not very active as well* (Fig. 5): *79% of the agents performed no more than two “for” or “against” actions.*

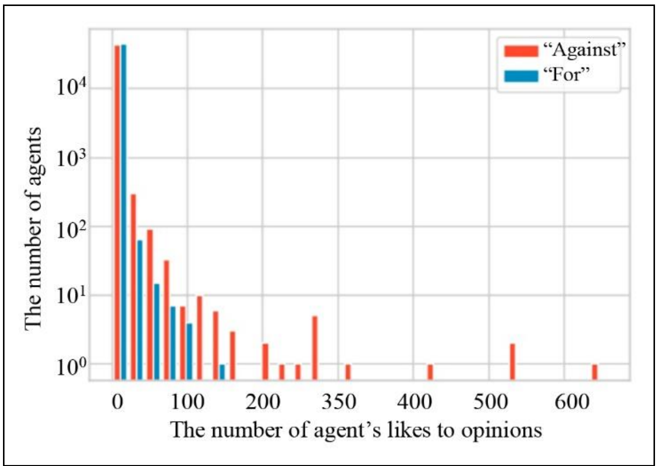

Fig. 5. The distribution of agents by the number of actions.

Of interest is the time interval between successive expressions of the agents’ opinions in the comments or the “probability”[6] of expressing an opinion again within a certain period (Fig. 6). As it turned out, if an agent expressed an opinion again, he did so with the following probabilities: 0.5 within a day, 0.7 within a week, and 0.8 within three weeks.

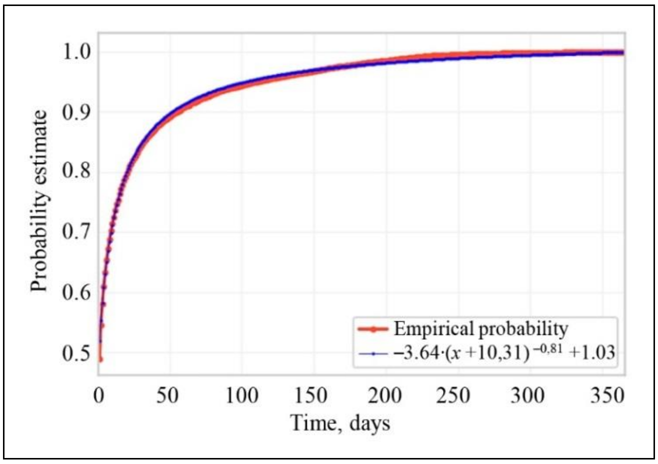

Fig. 6. The estimated probability of expressing an opinion again depending on the time interval. The blue graph is the approximation by the power function.

This result can be easily explained: an agent is involved in discussing new information occasions; as a rule, one occasion is discussed during a day, and the agents involved in the discussion can express their opinions more than once.

3.2 The dynamics of “public” opinion in the network

Let us consider the dynamics of discussions at the macro level. Figure 7 shows the dynamics of the number of agents’ opinions on wearing masks (the assessments of comments). The data were smoothened using the 3-day moving average.

On average, the agents posted 42 “for” comments per day (a median of 30, a maximum of 272), 59 “against” comments (a median of 41, a maximum of 419), and 46 neutral/irrelevant comments (a median of 26, a maximum of 409). *The peaks of activity come at the moments of restrictions*. In particular, on March 25, 2020, President Vladimir Putin addressed Russians and announced the introduction of the first off-work period due to COVID-19; in October 2020, repeated restrictions were introduced in response to the growing incidence (e.g., access to entertainment venues was restricted on October 19). Of course, another explanation is possible: *agents’ activity was connected with the objective picture of COVID-19 incidence in the Russian Federation*. To test such a hypothesis, we analyzed the incidence dynamics in the Russian Federation based on the *Johns Hopkins University* data [26]; see the graph in Fig. 8.

[6] Here the “probability” is the share of cases falling in a selected time interval (i.e., an estimated probability).

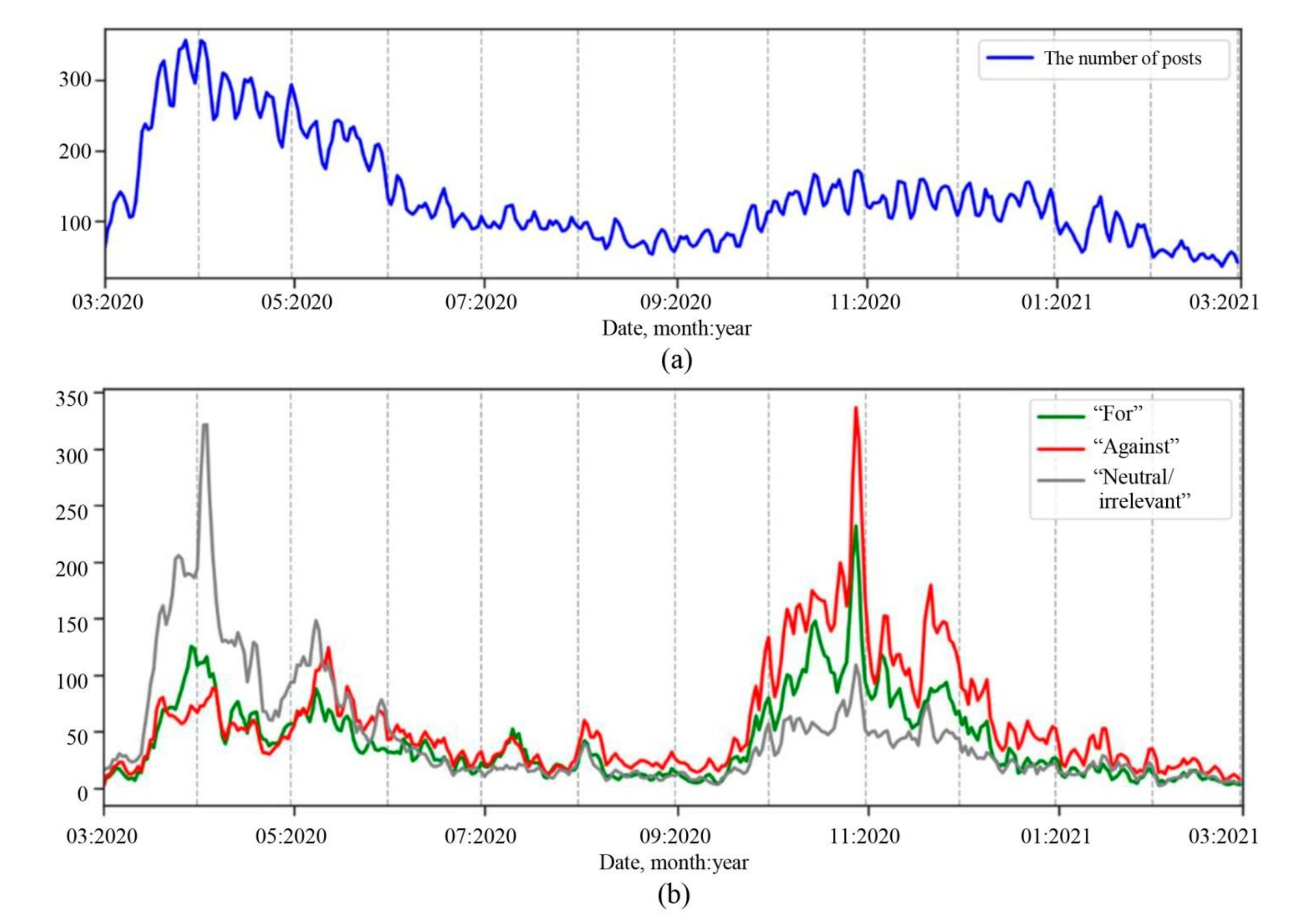

Fig. 7. The dynamics of activity on the issue of wearing masks in *VKontakte*: (a) the number of posts[7] and (b) the number of comments.

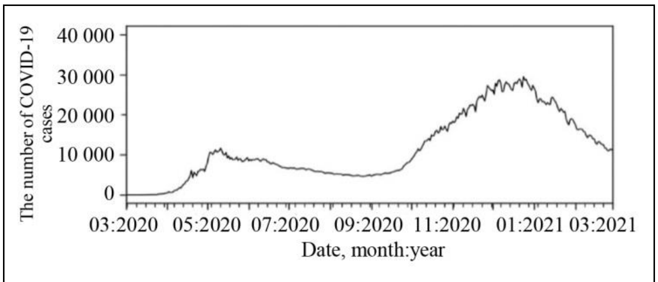

Fig. 8. The dynamics of COVID-19 incidence in the Russian Federation.

On average, there were 11.5 thousand cases per day (a median of 8.8 thousand and a maximum of 29.0 thousand) in the Russian Federation during the period under consideration. Pearson's correlation between incidence and the number of "for" opinions is 0.1 (a maximum of 0.5 is reached at a lag of 45 days, too large for a meaningful explanation); between incidence and the number of "against" opinions, 0.3 (a maximum of 0.7 is achieved at a lag of 45 days); between incidence and the number of "neutral/irrelevant" opinions, –0.3 (–0.2 at a lag of 38 days). Note the correlation between positive and negative (0.9), positive and neutral (0.6), and negative and neutral (0.4) messages. Consequently, *the social network activity on the "mask issue" is most likely indirectly related with COVID-19 incidence. To a higher degree, it is determined by informational events, including the agenda set by public authorities*: e.g., the measures to combat the pandemic.

How did attitudes to wearing masks change over time? As it turned out, *the share of "against" opinions increased* (Fig. 9*a*): by 21% in one year. The share of "against" actions changed even more (Fig. 9*b*): by 23% in one year.

At the same time, the share of "for" and "against" opinions increased in the total number of relevant opinions: it increased by 30% in one year. The share of "for" and "against" actions also increased (by 36%). In other words, we observe *the growing polarization in the network*.

[7] According the random check results, the posts of information sources were neutral on the issue of wearing masks.

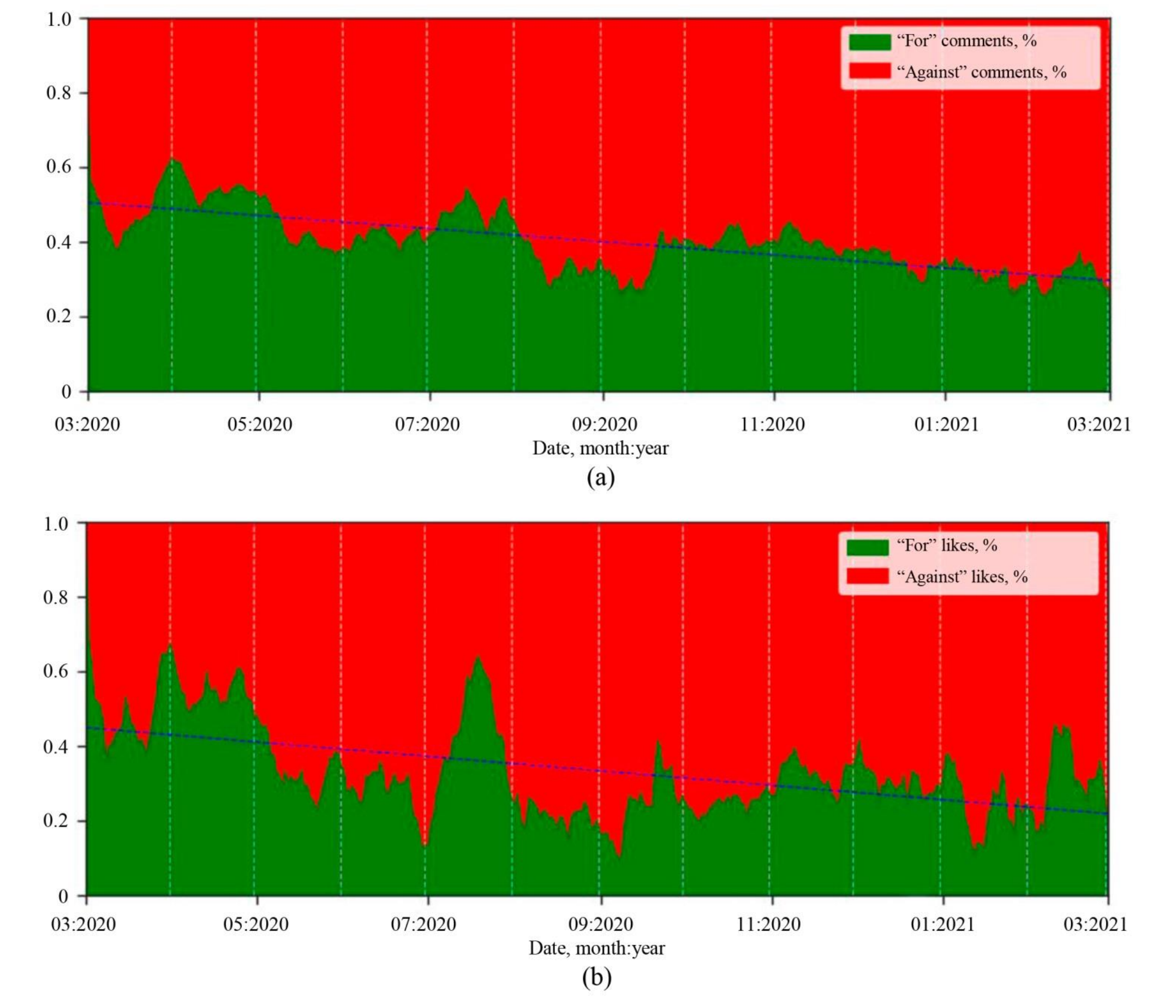

Fig. 9. The shares of: (a) "for" opinions (green area) and "against" opinions (red area) and (b) "for" actions and "against" actions.

3.3 The information interaction of agents

For the agents who responded to the posts of information sources, we construct the following networks of information interactions:

- G , the comments–likes network;
- G_C, the comments network;
- G_L, the likes network.

The network G is connected, it consists of 955 thousand nodes and 5216 thousand interaction links. The network G_C has 878 thousand comment links, and the network G_L has 4522 thousand like links.

The distribution of agents of the network G by degrees is shown in Fig. 10. Note the *power-law* nature of the dependence. The slope of the "straight line" differs for the in-degrees (d^-) and out-degrees (d^+): *a considerable number of agents have high "popularity" (the distribution of d^+); at the same time, there are significantly fewer agents with large "activity" (the distribution of d^-)*. The densities of degrees are demonstrated in Fig. 10*b* and *c*. Also, the empirical density was approximated by known heavy-tailed distributions (the power law $f(x) \propto x^{-\alpha}$ and the power law with an exponential cutoff $f(x) \propto x^{-\alpha} e^{-\lambda x}$, as the most appropriate ones). The power law, especially with cutoff, describes well the popularity of agents but not their activity.

What are the peculiarities of interaction between agents with different positions on wearing medical *masks?* Let us define an agent's position as the average of the opinions expressed in his actions (see the notations in subsection 3.1). According to Fig. 11, *for the most part, agents take polar positions* (even after eliminating the agents who committed a single act with the "for" or "against" opinion).

The natural question arises: *do agents prefer to interact with like-minded persons?* The answer is important for assessing the informational influence of the environment on opinions in the network.

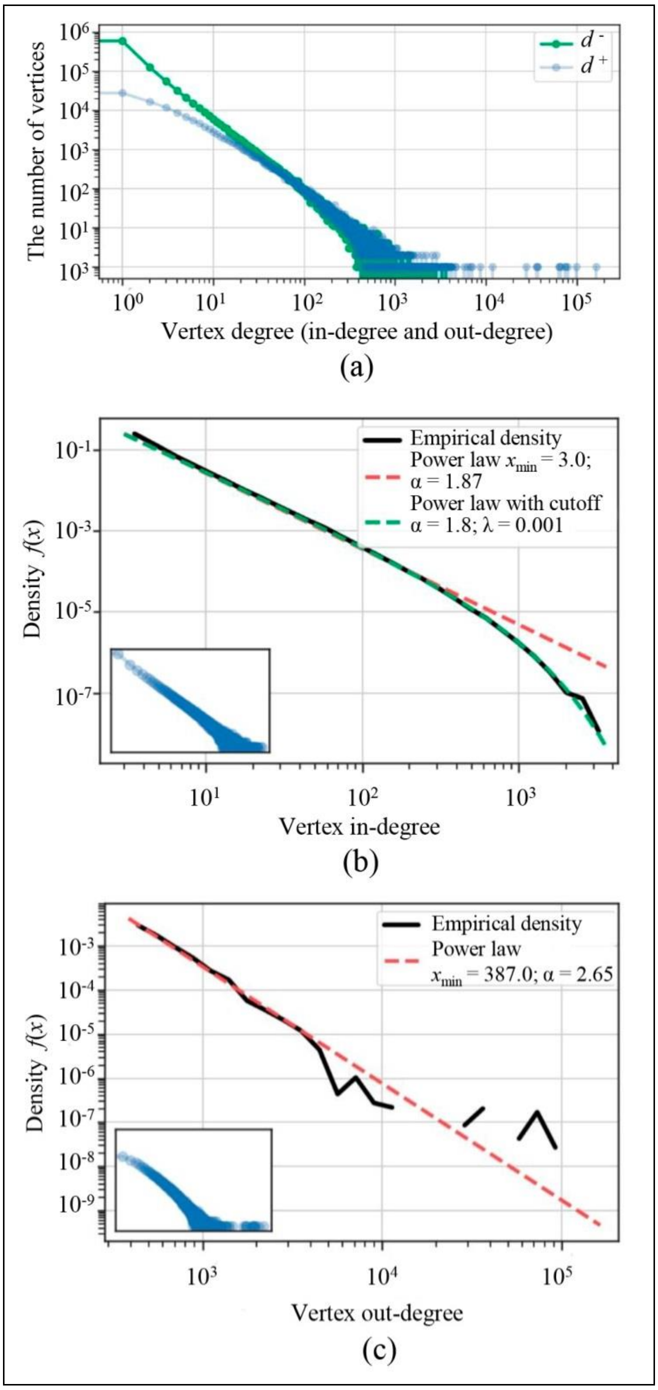

Fig. 10. The distribution of agents in the network: (a) by in-degree d^- and out-degree d^+, (b) by in-degree d^- and (c) by out-degree d^+.

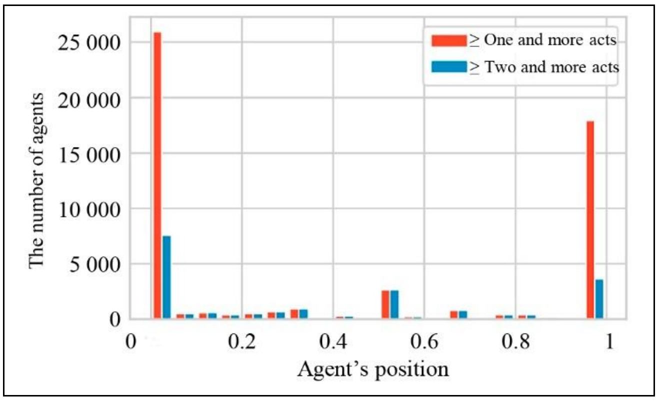

Fig. 11. The distribution of agents by their position.

Table 1 contains the values of *the assortativity coefficient* [27] (its range [–1.0, 1.0]) for the agents who committed at least one "for" or "against" act (52.8 thousand ones) and for the agents who committed at least four "for" or "against" acts (8.5 thousand).

Table 1

The assortativity coefficient for networks

The number of acts	G	G_C	G_L
At least 1	0.21	–0.01	0.25
At least 4	0.24	–0.05	0.31

Therefore, agents (especially active ones) prefer to like agents with a similar position on wearing medical masks. However, such preferences are not pronounced, and there is no particular preference for commenting on agents with a certain position.

Now, we consider the likes network for the agents who committed at least four "for" or "against" acts. In this network, the "for" position is taken by 30% of agents (p = 0.30) and the "against" position by 64% of agents (q = 0.64). For a randomly chosen edge, the estimated probability that it links agents with different positions is $2pq$ = 0.38. At the same time, the share of such edges in the network is 0.24. The inequality 0.24 < 0.38 confirms the weak assortativity of this network.

Let us calculate probabilities for the "cause-effect" relations in the likes network (Table 2). We introduce the following notations for the events: A_+ (A_-) means that for a randomly chosen link, the agent causing likes has the "for" position (the "against" position, respectively); B_+ (B_-) means that for a randomly chosen link, the agent making likes has the "for" position (the "against" position, respectively).

According to Table 2, the agents with the "against" position prefer to interact with agents with a similar position. (They both influence and are influenced by like-minded persons.) At the same time, for the agents with the "for" position, the interlocutor's position is not so important.

Table 2

Estimated conditional probabilities for like links

$P(B\|A)$	B_-	B_+
A_-	0.78	0.17
A_+	0.47	0.46

$P(A\|B)$	A_-	A_+
B_-	0.76	0.19
B_+	0.44	0.49

However, we cannot conclude that the agents in the likes network are divided into weakly interacting communities based on their positions: for such a partition, the modularity value [28] is 0.12. The conclusion is confirmed by visualizing the largest connectivity component of this graph; see Fig. 12. For comparison, the partitioning of the network into communities using greedy modularity maximization [29] yields a value of 0.52. (The maximum possible value is 1.0.)

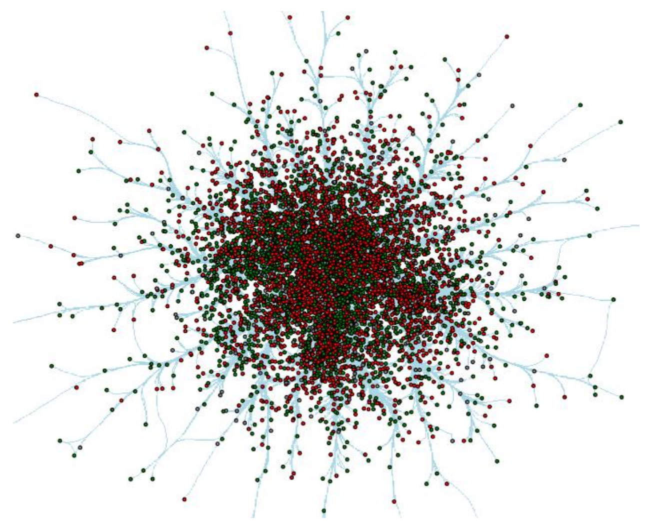

Fig. 12. The graph of likes between agents who committed at least four "for" or "against" acts. (The agents with the "for" position are marked in green whereas those with the "against" position in red.)

Consequently, agents do not form echo chambers (communities of like-minded persons) even when considering only the like links (the highest assortativity coefficient). The agents are influenced by the environment with different positions and can change their position after the influence.

4. THE RELATIONSHIP BETWEEN THE OPINIONS AND ACTIONS OF AGENTS

Let us pose the following questions:

- Are there agents who changed their opinions?
- Does the agent's opinion affect his actions?
- Do the agent's actions affect his opinion?

(See the Introduction.)

These questions are essential to identify the models of opinion/action dynamics. We try to answer them below.

4.1 The agents who changed their opinions

To identify and model the agents who changed their opinions (Question no. 2 in the Introduction), we need to select agents with suitable activity. Consider the agents with the following features:

– Each of them expressed at least one "for" opinion and one "against" opinion on wearing medical masks.

– Each of them expressed his opinion 10 to 100 times. (The weak activity of network agents has been emphasized in subsection 3.1: the majority of agents expressed their opinions and performed actions not more than twice during the period under consideration.)

– Each of them has an open social network profile and at least five friends (required to assess the sociodemographic characteristics of agents and the influence of friends).

These conditions are satisfied for 162 agents (*about 1% of the agents with the "for" or "against" opinion*). They will be called *significant agents*. Note that relaxing the second condition does not appreciably increase the number of significant agents (Fig. 13); however, in this case, the data on each agent become insufficient for the purposes of analysis and modeling.

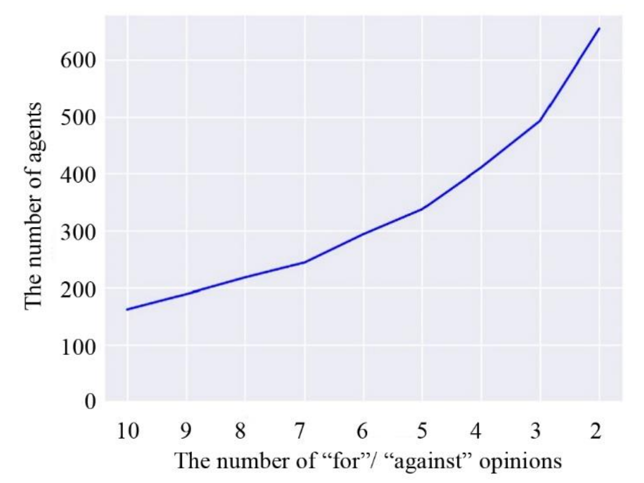

Fig. 13. The distribution of agents by the number of "for" or "against" opinions. (The horizontal line corresponds to the minimum number of opinions for an agent.)

Thus, although there are agents who changed their opinion during the period (some did that twice and more), their share is small. Examples of the opinion dynamics of significant agents are shown in Fig. 14. (The horizontal axis corresponds to time and the vertical axis to the opinion in the range [–1, 1]; "for" opinions are marked in green and "against" opinions in red.)

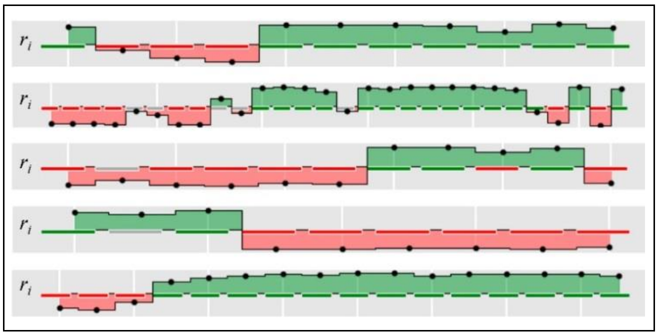

Fig. 14. The opinion dynamics of significant agents: some examples.

We characterize the significant agents: define their socio-demographic characteristics and build networks of links between them (the networks of friendship, comments, and likes).

The socio-demographic characteristics of significant agents. For most of the significant agents (99 agents or 61%), the age was not specified. The same situation is with the initial sample of agents with opinions (the age was not specified for 62% of agents).

The distribution of the other agents by age is presented in Fig. 15. The age of half of the significant agents does not exceed 47 years (38 years for the agents with opinions). The average age is 48 years (42 years for the agents with opinions). Consequently, *the significant agents are older than those with opinions*.

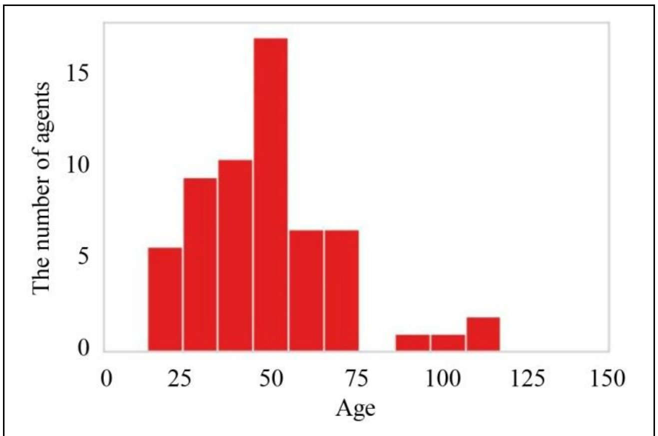

Fig. 15. The distribution of significant agents by age.

According to Fig. 16, the city was not specified for 25% of the significant agents (for 34% of the agents with opinions); 23% of the significant agents specified St. Petersburg (12% of the agents with opinions), 17% of the significant agents specified Moscow (13% of the agents with opinions), and 10% of the agents specified Yekaterinburg (6% of the agents with opinions). Thus, *significant agents prefer to specify the city to a greater extent; for significant agents, the share of their representatives from St. Petersburg and Yekaterinburg is higher*.

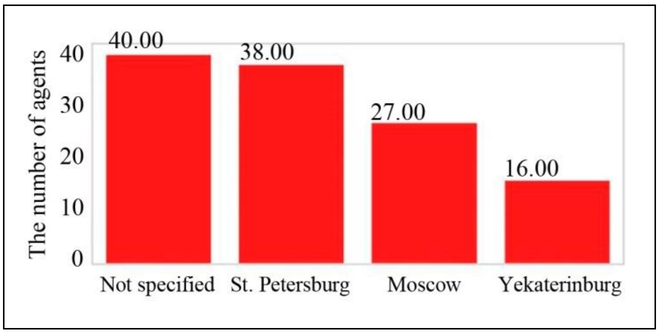

Fig. 16. The distribution of significant agents by the city of residence.

Among the significant agents, the majority belong to males (93 or 57.4%). At the same time, there are 59.6% of males among the agents with opinions. Based on the binomial test results, we do not reject the null hypothesis of equal distributions.

The networks of significant agents. *In the friendship network* of significant agents, there are only 17 links and most of the vertices (138) are isolated (Fig. 17). The green-color vertices correspond to the agents who generally have the "for" opinion and the red-color ones to those with the prevailing "against" opinion.

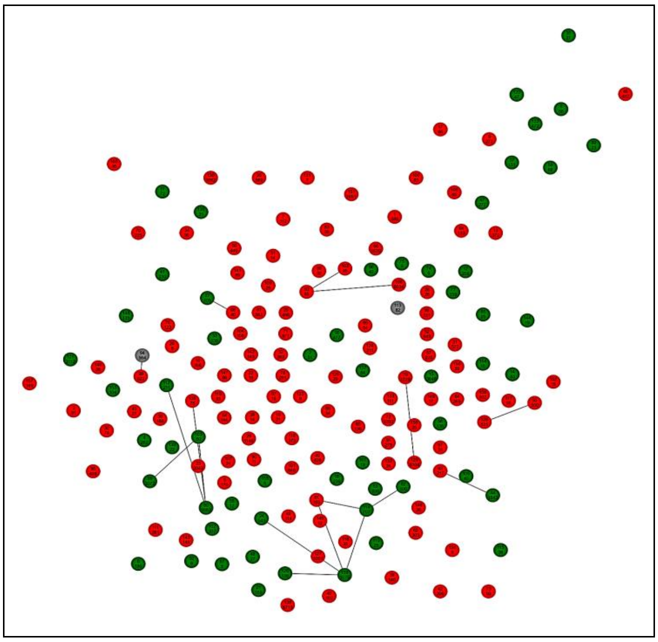

Fig. 17. The friendship network of significant agents.

The assortativity coefficient for the friendship network is 0.32: with some reservation, due to the small number of links, friendship can be assumed an indicator of the similarity of the agents' positions. On average, a significant agent has 432 friends, and half of the significant agents have no more than 113 friends (which is quite close to Dunbar's number).

In the comments network, significant users have 157 friendship links and 45 nodes are isolated (Fig. 18).

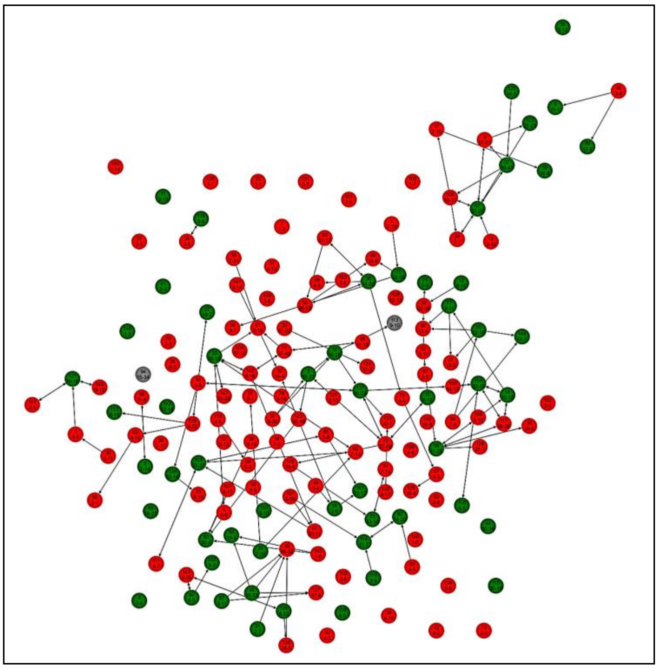

Fig. 18: The comments network of significant agents.[8]

The assortativity coefficient for the network is –0.46: *significant agents with opposite positions prefer to comment on each other*. On average, a significant agent is commented by 10 significant agents and, in turn, he comments on 13 significant agents; every second significant agent is commented by at most 7 significant agents and, in turn, every second significant agent comments on at most 10 significant agents.

In the likes network of significant users, there are 248 friendship links and 37 vertices are isolated (Fig. 19).

The assortativity coefficient for the network is 0.58: *significant agents with a similar position receive likes from each other*. On average, a significant agent receives likes from 69 significant agents and, in turn, he likes 28 significant agents; every second agent receives likes from at most 39 significant agents and, in turn, he likes at most 13 significant agents.

[8] Vertex positions are the same for all networks of significant agents: the friendship network, the comments network, and the likes network.

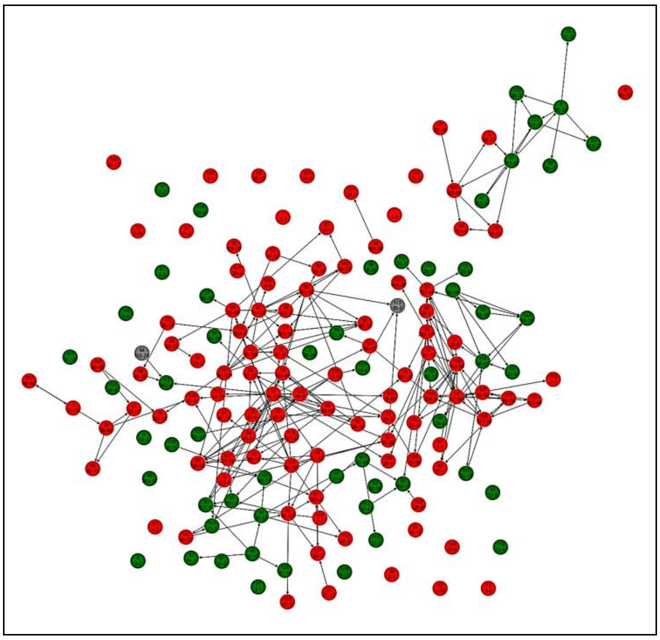

Fig. 19. The likes network of significant agents.

4.2 The influence of opinions on actions

Let us consider the opinion dynamics of agent $i \in N$ with a *position* and consecutive instants $t_m \in T$, $m = \overline{1, M_i}$, of expressing his opinions. (For each m, there exists a comment $a \in \delta_i$ such that $r'(a) \in \{0, 1\}$, $f_k(a) = 1$, $f_t(a) = t_m$.)

We define the set of "for" or "against" actions performed by agent i during the period $\tau = (t_m, t_{m+1}]$ between the expressed opinions with the numbers m and $(m + 1)$:

$$A_i^m = A_i(\tau) = \{a \in \delta_i \mid f_t(a) \in \tau,\ f_k(a) = 2,\ r'(a) \in \{0, 1\}\}.$$

To assess the influence of an agent's opinion on his actions, we introduce the *consistency degree*

$$1 - \frac{1}{M_i} \sum_{m \in \overline{1, M_i}} \left| r_i^{(")m} - \frac{\sum_{a \in A_i^m} r''(a)}{\left|A_i^m\right|} \right| \in [0, 1],$$

where $r_i^{(")m}$ is the opinion expressed in a comment a such that

$$r''(a) \in \{0, 1\},\ f_t(a) = t_m,\ f_a(a) = i.$$

In a practical interpretation, *consistency* (see Question no. 1 in the Introduction) reflects how much the agent's actions coincide (correlate) with his opinions.

Figure 20 shows a histogram of the distribution of agents by the consistency degree (for the agents who expressed at least five opinions).

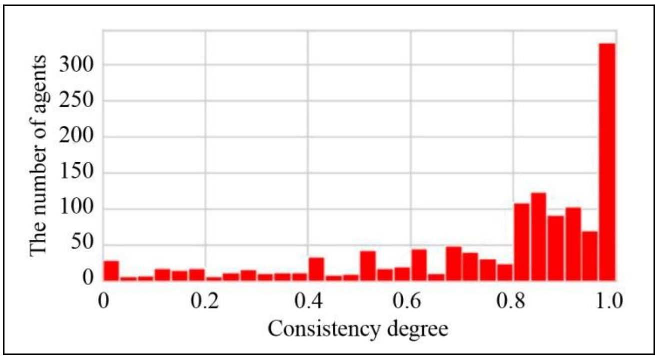

Fig. 20. The distribution of agents by the consistency degree.

The consistency degree averaged over the entire network is 0.76 (when restricting the number of expressed opinions, 0.73). *In general, the agent's actions are "consistent" with his opinion, i.e., the agent's opinion can "influence" his actions*.

4.3 The influence of actions on opinions

Let us assess this influence, thereby partially answering Question no. 5. We define the set of actions performed by agent i during a given period $\tau=[t_m,t_{m+1})$:

$$B_i(\tau)=\{a\in\delta_i \ |r'(a)\in\{0,1\},\ f_t(a)\in\tau,\ f_k(a)=2\}.$$

Also, we define the influence of the agent's actions on his opinion:

$$r_{D_i}(\tau)=\frac{\sum_{b\in B_i(\tau)} r(b)}{|B_i(\tau)|}\in[-1,1].$$

Assume that an opinion change is *significant* if it exceeds the threshold $\epsilon=0.1$. By analogy with [30], we consider the "probability"[9] of an agent's significant opinion change under the influence of his actions. Let all possible scenarios of expressing the agent's consecutive opinions, $t_m \rightarrow t_{m+1}$, be divided into five classes based on his "initial" opinion:

– "strongly against," $r \in [-1, -0.6]$;
– "moderately against," $r \in (-0.6, -0.2]$;
– "weakly expressed position," $r \in (-0.2, 0.2]$;
– "moderately for," $r \in (0.2, 0.6]$;
– "strongly for," $r \in (0.6, 1]$.

For each class, we estimate the probabilities of the following events: (*a*) the agent's opinion will significantly change "towards" his actions and (*b*) the agent's opinion will significantly change in the opposite direction to his actions. Here are the analysis results for two classes, "strongly against" and "strongly for." (The cardinalities of the other classes turned out to be too small.) Figure 21 shows the estimated probabilities of a significant opinion change under the influence of actions: towards actions (blue) and in the opposite direction (red).

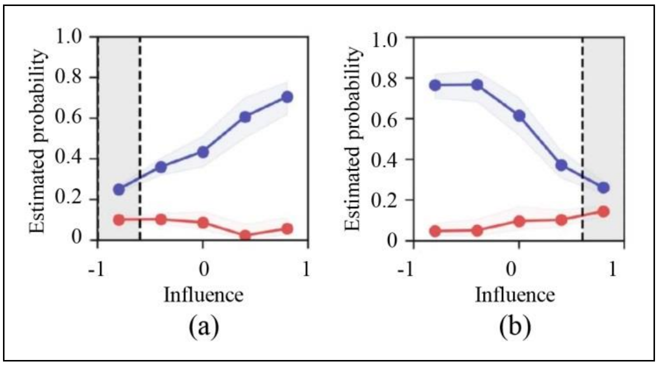

Fig. 21. The estimated probabilities of significant opinion changes for two classes: (a) "strongly against" and (b) "strongly for."

Note. If the agent performed no action between the expressed opinions, the influence is supposed to be 0.

Figure 22 demonstrates the mean and confidence intervals (at a significance level of 0.05) for a significant opinion change due to the influence of actions.

Consequently, if agents change their opinions, they do it most often towards their actions. The greater the difference between the "initial" opinion and the agent's actions is, the higher the probability of opinion change will be (Fig. 21) and the greater magnitude the opinion change towards actions will have (Fig. 22).

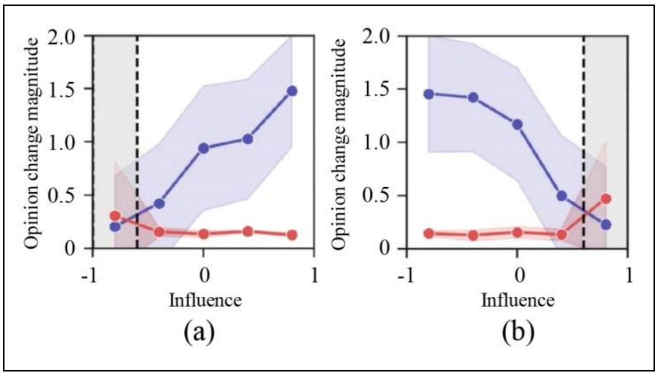

Fig. 22. The magnitude of significant opinion changes for two classes: (a) "strongly against" and (b) "strongly for."

CONCLUSIONS

This paper has presented a primary analysis of the joint dynamics of the opinions and actions of social network agents (*VKontakte* users) on an example of their attitude toward wearing medical masks during the first year of the COVID-19 pandemic.

[9] An interpretation for the share of cases with a significant opinion change.

The opinions of *VKontakte* users have been identified. A satisfactory quality of automatic classification, with an accuracy index of 0.82, has been achieved using deep learning methods.

The network agents with a pronounced position on wearing medical masks have been characterized. As has been discovered, *VKontakte* users are polarized: on the one hand, the share of agents with the "for" position significantly exceeds that of agents with the "against" position; on the other hand, the activity of agents with the "against" position is higher. In general, there is an activity misbalance: the agents are inactive but a small number of agents demonstrated very high activity. If an agent expresses his opinion again, he will do so within a day with probability 0.5. This fact can be explained as follows: agents are involved in discussing new information occasions and the old ones are forgotten.

The dynamics of activity of network agents relevant to wearing masks have been analyzed. The network activity dynamics are characterized by bursts, as a rule, associated with informational events (e.g., the introduction of measures to combat the pandemic). No direct relationship with COVID-19 incidence has been found (most likely, it is implicit). We have found the growing polarization of the network over time (a 30% increase in the number of polarized opinions in one year). The "for"-"against" opinions ratio changed in favor of the negative opinions (a 20% increase in one year).

The networks of information interaction of agents have been examined. In these networks, there are no particular preferences for commenting on agents with a certain position. Agents (especially active ones) prefer to like agents with a similar position regarding wearing masks, but such preferences are not pronounced. However, for the likes network, agents with the "against" position prefer liking agents with a similar position. (They influence like-minded persons and are themselves influenced by them.) At the same time, for agents with the "for" position, the interlocutor's position is not so important. Nevertheless, the agents in the likes network are not in the echo chambers of like-minded persons: the modularity coefficient is too low. This result has been also confirmed by visualizing the network of informational interactions. Hence, agents are exposed to the cross-influence of the social environment and can change their opinions. Therefore, the models of informational influence in social networks should be studied further.

Some important issues have been settled to identify the models of opinion/action dynamics in the future. First, we have confirmed the existence of a small number of agents (called *significant*) who changed their opinion during the period under consideration; see Question no. 2 in the Introduction. They constitute about 1% of the number of agents with "for" or "against" opinions. The analysis of their characteristics has demonstrated the following: there are more males among the significant agents (57%); significant agents are older; the share of significant agents from St. Petersburg and Yekaterinburg is higher compared to those with opinions. Significant agents are weakly connected by friendship links; they prefer to comment on significant agents with opposing positions and like significant agents with similar positions (see Question no. 3). Second, it has been shown that an agent's opinion (his internal state) influences his actions, which are, in turn, "consistent" with the opinion (see Question no. 1). Third, as it has turned out, agents' opinions change towards their actions: the greater the difference between the "initial" opinion and the agent's actions is, the more likely the agent will change his opinion towards his actions and the greater magnitude this change will have (see Question no. 5).

In part II of the study, formal linear models of the joint dynamics of opinions and actions will be identified based on the results obtained (see Questions nos. 5–7). Part III, concluding the study, will be devoted to the identification of binary micro models and the comparison of linear and threshold models (see Questions nos. 4–7).

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REFERENCES

1. Gubanov, D.A., Influence in Social Networks: Formalization Variants, *Large-Scale Systems Control*, 2020, no. 85, pp. 51–71. (In Russian.)
2. Chkhartishvili, A.G., Gubanov, D.A., and Novikov, D.A., *Social Networks: Models of Information Influence, Control and Confrontation*, Cham: Springer, 2019.
3. Gubanov, D.A. and Chkhartishvili, A.G., Meta-Agent and User Influence Levels in a Social Network, *Control Sciences*, 2016, no. 6, pp. 12–17. (In Russian.)
4. Breer, V.V., Novikov, D.A., and Rogatkin, A.D., *Mob Control: Models of Threshold Collective Behavior*, Cham: Springer, 2017.
5. Gubanov, D., A Study of a Complex Model of Opinion Dynamics in Social Networks, *Journal of Physics: Conference Series*, 2021, vol. 1740, pp. 1–6.
6. Allbaracin, D. and Shavitt, S., Attitudes and Attitude Change, *Annu. Rev. Psychol.*, 2018, vol. 69, no. 4, pp. 1–29.
7. Banisch, S. and Olbrich, E., Opinion Polarization by Learning from Social Feedback, *The Journal of Mathematical Sociology*, 2019, vol. 43, pp. 76–103.

8. DeGroot, M., Reaching a Consensus, *Journal of American Statistical Association*, 1974, no. 69, pp. 118–121.
9. Granovetter, M., Threshold Models of Collective Behavior, *The American Journal of Sociology*, 1978, vol. 83, no. 6, pp. 1420–1443.
10. Hunter, J., Danes, J., and Cohen, S., *Mathematical Models of Attitude Change*, Orlando: Academic Press, 1984.
11. Schelling, T., *Micromotives and Macrobehaviour*, New York, London: Norton & Co Ltd, 1978.
12. Xia, H., Wang, H., and Xuan, Z., Opinion Dynamics: A Multidisciplinary Review and Perspective on Future Research, *Int. Journal of Knowledge and Systems Science*, 2011, vol. 2, no. 4, pp. 72–91.
13. Zimbardo, P.G. and Leippe, M.R., *The Psychology of Attitude Change and Social Influence*, Mcgraw-Hill, 1991.
14. Myers, D., *Social Psychology*, 11th ed., McGraw-Hill Education, 2012.
15. Cialdini, R.B., *Influence: The Psychology of Persuasion*, Harper Business, 2006.
16. Pandemic Profiteers: the Business of Anti-vaxx, Center for Countering Digital Hate (CCDH), 2021. URL: https://www.counterhate.com/_files/ugd/f4d9b9_13cbbbef105e459285ff21e94ec34157.pdf.
17. Novikov, D.A. Dynamics Models of Mental and Behavioral Components of Activity in Collective Decision-Making, *Large-Scale Systems Control*, 2020, no. 85, pp. 206–237. (In Russian.)
18. Gubanov, D., Kozitsin, I., and Chkhartishvili, A., COVID-19 Information Consumption and Dissemination: A Study of Online Social Network VKontakte, *Proceedings of the 14th International Conference "Management of Large-Scale System Development"* (*MLSD 2021*), Moscow, 2021, pp. 1–5. URL: https://ieeexplore.ieee.org/document/9600199.
19. Gubanov, D., Kozitsin, I., and Chkhartishvili, A., Face Mask Perception during the COVID-19 Pandemic: An Observational Study of Russian Online Social Network VKontakte, *Advances in Systems Science and Applications*, 2021, vol. 21, no. 3, pp. 91–100.
20. Kuratov, Y. and Arkhipov, M., Adaptation of Deep Bidirectional Multilingual Transformers for Russian Language, *arXiv:1905.07213*, 2019.
21. Babakov, N., Logacheva, V., and Panchenko, A., Beyond Plain Toxic: Detection of Inappropriate Statements on Flammable Topics for the Russian Language, *arXiv:2203.02392*, 2022. DOI: https://doi.org/10.48550/arXiv.2203.02392.
22. Grigoriev, O., Kuznetsova, Y., Nikitina, E., et al., Causative-Emotive Analysis. Part I. Emotional Reactions of Social Networks Users Research, *Psikhologich. Zh.*, 2022, no. 3 (43), pp. 114–121. (In Russian.)
23. Nugamanov, E., Loukachevitch, N., and Dobrov, B., Extracting Sentiments towards COVID-19 Aspects, *CEUR Workshop Proceedings*, Moscow, 2021, pp. 299–312.
24. Pronoza, E., Panicheva, P., Koltsova, O., and Rosso, P., Detecting Ethnicity-targeted Hate Speech in Russian Social Media Texts, *Information Processing and Management*, 2021, vol. 58, no. 6, art. no. 102674.
25. Howe, N. and Strauss, W., *Generations: The History of America's Future, 1584 to 2069*, New York: William Morrow & Company, 1991.
26. Dong, E., Du, H., and Gardner, L., An Interactive Web-based Dashboard to Track COVID-19 in Real Time, *Lancet Inf. Dis.*, 2020, vol. 20(5), pp. 533–534.
27. Newman, M., Mixing Patterns in Networks, *Physical Review E*, 2003, no. 2 (67), p. 026126.
28. Newman, M., Modularity and Community Structure in Networks, *Proceedings of the National Academy of Sciences of the United States of America*, 2006, vol. 103, no. 23, pp. 8577–8696. URL: https://arxiv.org/abs/physics/0602124v1.
29. Clauset, A., Newman, M., and Moore, C., Finding Community Structure in Very Large Networks, *Physical Review E*, 2004, vol. 70, no. 6. DOI: 10.1103/PhysRevE.70.066111.
30. Kozitsin, I., Opinion Dynamics of Online Social Network Users: a Micro-level Analysis, *Journal of Mathematical Sociology*, 2021, pp. 1–41. DOI: https://doi.org/10.1080/0022250X.2021.1956917.

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