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Yuri G. Rykov, Peter A. Meylakhs,
Yadviga E. Sinyavskaya

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Yuri G. Rykov[1], *Peter A. Meylakhs*[2], *Yadviga E. Sinyavskaya*[3]

NETWORK STRUCTURE OF AN AIDS-DENAILISTS ONLINE COMMUNITY: IDENTIFYING CORE MEMBERS AND THE RISK GROUP

Background: With the rapid growth of online social network sites (SNS), the issue of health-related online communities and its social and behavioral implications have become increasingly important for public health and healthcare. Unfortunately, online communities often become vehicles for promotion of pernicious misinformation, for example, alleged harm of vaccination or that HIV-virus is a myth (AIDS-denialism). This study seeks to explore the social structure and participants' behavior of the AIDS-denialists online community to identify and estimate the those who potentially are most susceptible to AIDS-denialists arguments - "the risk group" in terms of becoming AIDS-denialists.
Methods: Social network analysis was used for examining the most numerous AIDS-denialist community in the most popular Russian SNA "VKontakte", which numbered 13 000 – 15 000 members during the various stage of analysis. Qualitative content analysis was also used for collecting relevant for this study members' attributes, such as HIV status and the extent of belief in AIDS-denialists arguments. Two datasets were collected to analyze friendship relations between community members and their communication relations.
Results: Using social network analysis combined with content-analysis we have identified the core of online community - cohesive and dedicated AIDS-denialists, and the risk group, which is not equal in composition to all peripheral members appeared in the online group. The risk group is the circle of users who engage with core members through online communication and may be more susceptible the AIDS-denialist propaganda. Analysis allowed to significantly reduce the target audience for possible intervention campaign and simultaneously increase the accuracy of user selection into the risk group (1369 users from the risk group is more than 10 times less than whole online group population counting over 15 000 users). Thus, online information interventions should be aimed at this risk group audience in the first place to prevent their adoption of AIDS-denialism beliefs, further spread of AIDS-denialism, and pernicious health consequences associated with being an HIV-positive AIDS-denialist.
Conclusion: More research on influence of AIDS-denialism on HIV-positive online group members is needed. Of particular interest are longitudinal or case control studies that could detect the size of effect of AIDS-denialist propaganda that is communicated from hard-core denialists to the risk group, different factors associated with higher or lower susceptibility to AIDS-denialist views, and real health behavior change that occurs with becoming an AIDS-denialist.

Keywords: online community, HIV/AIDS, online social networks, social networks analysis, social contagion, risk groups

JEL classification: Z19, I12

[1] National Research University Higher School of Economics, St. Petersburg School of Social Sciences and Humanities, The Laboratory for Internet Studies. yrykov@hse.ru
[2] National Research University Higher School of Economics, St. Petersburg School of Economics and Management, International Centre for Health Economics, Management, and Policy. pmeylakhs@hse.ru
[3] National Research University Higher School of Economics, St. Petersburg School of Social Sciences and Humanities, The Laboratory for Internet Studies. ysinyawskaya@hse.ru

Introduction

With the rapid growth of online social network sites (SNS), the issue of health-related online communities and its social and behavioral implications have become increasingly important for public health and healthcare [Centola, 2013]. The general topic of this studies is the interplay between the Internet use and public health, i.e. public health relevant implications from participation in online health-related communities. Such research focuses not only on positive outcomes of online groups use such as strong emotional support [Chung, 2014] but also on cases of misinformation and pernicious health practices spreading via the Internet and online social networks like well-known anti-vaccination or pro-anorexia movement [Yom-Tov, & boyd, 2014], which can undermine public health policy.

This work continues and complements the previous study of the AIDS-denialists online community in Russian SNS "VKontakte" (or *VK.com*) [Meylakhs et al., 2014]. The AIDS-denialists is a movement, which denies either human immunodeficiency virus (HIV) existence or causal relationship between HIV and AIDS. Frequently AIDS-denialists beliefs lead people who live with HIV (PLWH) to refuse HIV treatment, which results in HIV related diseases and death from AIDS.. Thus, AIDS-denialists community on the Internet and on SNS in particular represents a serious public health threat, associated with higher morbidity and mortality from AIDS and HIV-related diseases, and the spread of HIV among population.

Previous research [Meylakhs et al., 2014] which was based on qualitative approach and netnography methods has revealed a number of rhetorical strategies of persuasion which is used by the AIDS-denialists to influence newcomers at the AIDS-denialists communities (in the form of SNS “groups”) previously described in [Meylakhs et al., 2014]) and on those group members and lurkers, who doubt the HIV science and are at risk to become AIDS-denialists (doubting users). However, not all group members and visitors are equally susceptible to AIDS-denialists’ propaganda. Thus, this study seeks to explore the social structure and participants' behavior of the AIDS-denialists online community to identify and estimate the those who potentially are most susceptible to AIDS-denialists arguments - “the risk group” in terms of becoming AIDS-denialists. In order to do that we need to analyze the network structure of the AIDS denialist community in question.

There are also practical grounds for the research objective. Information campaigns and public health interventions which use the Internet as a delivery platform are one of the most common ways for struggle against the spread of HIV[Bennett, & Glasgow, 2009]. According to Noar et al. [Noar et al., 2009] audience targeting and segmentation techniques should be used to

increase effectiveness of such interventions. SNS have been already used for HIV prevention interventions [Jaganath et al., 2012]. Therefore, relatively accurate detection of risk group in terms of becoming AIDS-denialists can be very helpful for media campaigns that are directed against AIDS-denialism on SNS in Russia and former Soviet Union countries.

Literature review

Network analysis of online health communities

Online health-related groups are created around a lot of medical issues, including cancer, diabetes, HIV/AIDS, smoking, obesity, depression, etc. There are several types of online health communities. The most frequent one is online support and patient self-help groups, for instance, cancer patients [Setoyama et al., 2011] or PLWH support communities [Bar-Lev, 2008; Coursaris, & Liu, 2009; Mo, & Coulson, 2008; Shi, & Chen, 2014]. Doctors and health care professionals as well as patients become members of these communities, prompting 'doctor - patient' communication [Santana et al, 2010]. Other studies focus on social movements in the domain of public health, particularly on HIV/AIDS [Vijaykumar et al, 2014] or (anti)vaccination movements [Kata, 2012]. Research on these communities mostly focuses on users' online behavior and interactions as well as on the effects and health outcomes of communication depending on its intensity, and participants' and content's characteristics. Another type is communities for knowledge sharing among healthcare professionals: doctors, nurses, pharmacists and even researchers [Hara, & Hew, 2007; Stewart, & Abidi, 2012].

There are numerous studies that use social network analysis (SNA) to explore community structure and interaction among participants in these diverse health-related online groups. The study by Cobb et al. [Cobb et al., 2010] was devoted to the smoking cessation community. Authors found that friendship and communication networks within the online forum are consistent with the core–periphery structure; and individual metrics of social network integration (e.g. centrality) were associated with increased likelihood of not smoking. Thus, smoking cessation behavior was associated with higher engagement with members of online forum.

Himelboim and Han [2013] examined the connectivity patterns of Twitter-following networks among users who post on prostate and breast cancer topics. They have found that these networks consist of two different types of communities which depend on a persistency of cancer-specific Twitter use and sources of information. Grassroots users (cancer-specific blogs and individuals), who tweet on the topic constantly, form 'core communities' and draw primarily on information sources related to breast or prostate cancer, while healthcare institutions, academic

organizations and celebrities, who post about cancer sporadically, form 'visiting communities'. The Twitter hubs in core communities do not include institutional sources like healthcare providers, that remain the most trusted information sources. *Therefore, the structure of twitter communities is related to members' characteristics and quality of health information sources*.

Chomutare et al. [Chomutare et al., 2013] studied commenting networks from several online forums devoted to diabetes. They found that users who were connected to each other in these networks form clusters based on similarity in personal attributes such as diabetes-type and years-since-diagnosis. Also they discovered that patients who were more experienced in coping with the disease (with more years-since-diagnosis) tend to be the most central and respected members, i.e. leaders in the community. It means *a few experts become an authority in the online community and act as mentors for the majority (up to 78%) of newcomers and newly diagnosed patients*. Chomutare et al. results demonstrates that SNA is a useful method to identify leaders and explore influence in online health forums.

Gruzd and Haythornthwaite [2013] analyzed the social media–supported group Health Care Social Media Canada on Twitter and found that the community is sustained by "a strong core of active participants including the group founder, who lead in posting and prominence in the network". Also they showed that attention-giving from the core to other group participants is an important feature of this community. Statistics on both inward and outward ties reveal community leaders because their messages receive the most feedback and they actively engage other users. Contrary to previous findings there is no tendency for connection based on similarity in professional status among community members. So this discussion community maintains a welcoming environment and stimulates knowledge exchange across professional boundaries.

Chen and Shi [2015] explored communication networks within an HIV/AIDS online group on the Chinese social media Weibo, and tested how the frequency and reciprocity of contacts impact on an amount of social support messages in user pairs. The results show that informational support increases in pairs with a greater intensity of communication as well as with a higher reciprocity rate. Emotional support grows only with the frequency of exchanged messages and does not depend on the reciprocity. *It means emotional support is provided even in asymmetric relationships*.

Stewart and Abidi [Stewart, & Abidi, 2012] studied communication patterns from a health care professionals discussion forum to better understand how the online community shares experiential knowledge. They showed that a small set of very active members (29% of the overall 46 forum members for 1-mode network) who had high centrality rankings and belonged

to the same cluster is dominating in the community. These core members also produce most of the content within the forum.

Thus, discovering the structure of user social ties and interaction within online health-related communities is used to understand interrelation between characteristics of online user behavior and some health conditions.

Spread of behavior and social contagion on networks

The other research tradition in the domain of health behavior is the studies of epidemics and behavior diffusion through social networks [Smith, & Christakis, 2008]. Behavioral phenomena like emotions or consumption can be seen to spread like an infectious disease, from one to another via face-to-face interaction or mediated communication. One of the most prominent works by Centola [Centola, 2010] showed how the network structure of who is connected to whom critically affects the extent to which a health behavior spreads across a population. The recent work demonstrated that social contagion concept can describe a spread of a wide variety of health-related behaviors like obesity [Christakis, & Fowler, 2007], smoking [Christakis, & Fowler, 2008], drug use [Mednick et al., 2010] or alcohol consumption [Rosenquist et al., 2010] through networks.

Participation in online communities provides an access to weak ties to others who have similar experience. The 'strength of weak ties' in the case of HIV/AIDS online groups may result in the effect of decreasing health-related uncertainty and increasing health condition predictability [Keating, & Rains, 2015]. Participation in an online AIDS-denialist community may increase awareness of patients over their health condition in the wrong way, i.e. persuade newcomers in favor of AIDS-denialist theory explaining HIV/AIDS. Adherence to AIDS-denialism beliefs is a just cognitive aspect of individuals but may cause further changes in real health behavior such as refusing HIV testing and treatment. The social contagion can be a mechanism of influence of AIDS-denialist beliefs; there is evidence of similar possibility of being influenced by these beliefs is based on studied outcomes of online health communities [Murthy et al., 2011; Boogaarts et al., 2014; Myneni et al., 2016]. *Thus, engaging into online AIDS-denialist community through communicative interaction with its core members raises a risk to be affected by these beliefs and has potential negative health outcomes.*

Research Questions

Studies of online communities have shown that a small group of users may have a significant amount of influence on other members. Identification of these users is helpful for understating the functioning of a community [Tang, & Yang, 2010] and can be useful in advocating new treatments, encouraging healthy lifestyles, and reaching other public health policy goals in general [Zhao et al., 2014]. Specifically for the AIDS-denialists online community a detection of core members means identification the source of influence in the group.

> *Research Question 1*: *What is the structure of the AIDS-denialists community? Is there a cohesive core of devoted AIDS-denialists or are members separate and disconnected from each other?*

The ultimate goal in the context of HIV/AIDS public health policy is decreasing the influence of AIDS-denialists and prevention of spread of AIDS-denialism beliefs. It is next to impossible to dissuade the leaders of this community from their views [Kalichman et al., 2010; Natrass, 2013]. Therefore, leaders of the online AIDS-denialists community are not the target audience for possible interventions but their detection helps to determine which community members may be affected by them. The analysis of communicative interaction between group leaders and other members allows us to detect and describe the risk group of users who are most likely to be affected by AIDS-denialist's persuasive communication.

> *Research Question 2*: *What is the risk group of AIDS-denialism ideas adopters from the social network and contagion theory perspective?*

Method

Data Collection

The object of this study is the largest online group representing the movement of AIDS-denialists on the most popular Russian SNS *VK.com*, which is open for everybody who is willing to join. At the beginning of this project this group counted about 13,000 members and by the end of the study it has grown to over 15,000 members. The group consists of a short description section with the mission and the group's rules; members list; the main message board called 'the wall' (posts from 'the wall' appear in the followers' news feeds); discussion boards for specific topics and sections for selected videos, audio tracks and references. Besides joining the group, users may post, comment and like group content and add each other to 'friend list'. The data on

users' activity and 'friendship' relations are stored on SNS server, are open and publically available. This research deals only with the data available from SNS server including data on user interaction and texts of posted messages. This data are available through application programming interface (API) of SNS server. The data was collected automatically with the aid of software specially designed for this project; the data collection involved several iterations.

Two datasets were collected to analyze friendship and communication relations. The first one is for 'friendship' network and includes: 1) the data from the group's 'wall' on users' activity in online group and the content posted on the wall (starting from the date of the earliest post, December 2, 2008 and until January 20, 2015); 2) the metadata of all active users (gender, age, geographical location, etc.); 3) the data on 'friendship' relations existing among the community participants.

The second one is for communication network and additionally includes: 1) the data from discussion boards on users' posting activity; 2) the data on communication interactions among users - 'likes' senders and receivers, comments senders and receivers, and users' mentioning. Both datasets were filtered by excluding deleted or banned user profiles.

Content-analysis

We have conducted a qualitative content-analysis of posts and comments to identify users' attributes relevant for our study: HIV-status and attitude towards AIDS-denialism beliefs. HIV-status attribute could be positive, negative or unknown/closured. Positive or negative HIV-status was assigned to user if we found a direct information on the status, such as a reference to HIV test results, mentioning years since HIV diagnosis or HIV treatment experience, for example, the following post:

I got "+" on the tenth week of my pregnancy.

Attitudes towards AIDS-denialism beliefs were split into 4 categories: devoted AIDS-denialists, doubting users, so called 'orthodox' users (users who believe in HIV science and whom AIDS-denialists dubbed 'orthodox') and users, whose HIV beliefs are could not be determined by the analysis ('unknowns'). Adherence to AIDS-denialism was assigned if user expressed resentment and mistrust with regards to doctors who treat HIV, AIDS centers or AIDS-metanarrative, that is, standard and one-size-fits-all picture of HIV and AIDS, devoid any nuances that is familiar from popular medical discourses [for more detailed explanation and analysis see Meylakhs et al., 2014]. In the following quote the informant justifies his AIDS

denialism by questioning the standard scenario of HIV progression, according to which an HIV infected person dies within 5-7 years.

a. They(doctors) have been saying to me for 15 years, that I'm going to die tomorrow!!!

'Doubting' (or 'suspicious' to HIV science) category was assigned to user, if she directly claimed that she is uncertain, which arguments – of AIDS-denialists or of those who supports accepted HIV-science were true,, or asked for advice, 'which road to take' – based on AIDS-denialism or HIV science:

a. People, so answer me, the illiterate, shall I continue taking pills or stop
b. I have HIV and it's time to decide whether to be registered or not.

An 'orthodox' category was assigned to user, if he expressed statements in favor of the official medical theory or against the group beliefs, for instance, demonstrated a positive attitude to HIV treatment:

I myself have taken therapy for 10 years, given birth to a healthy child, and who is not treated will die for sure 100%.

Network Analysis

First, we considered the 'friendship' network. Nodes in the network are users participating in the online group. Ties are mutual 'friend' relationships between them, so the network is undirected. Analysis of network characteristics was combined with personal activity rates as well as personal attributes such as HIV-status and attitude towards AIDS-denialism theory to identify the community's core. We examined how status of dissident is connected to user behavior within the group. 'Friendships' networks are important because they reflect the informal social structure of a group, its cohesion, partition and sub-communities composition. Also, 'friendships' relations reflect some kind of a trust and an amount of intra group social capital [Ellison et al., 2011; Ellison, & Boyd, 2013].

Second, we considered the communication network among core members and peripheral participants to identify the risk group. We assigned a tie between members in cases when one member comments on or likes a post (or a comment) left by the other, or also when one member mentions the other in his posting. Thus communication network is directed and weighted because members may exchange comments or likes repeatedly. Gephi software [Bastian et al., 2009] was used for network analysis, and R software - for statistical analysis.

Results

Identifying the community core of AIDS-denialists

We define a user's belonging to the online community by participation in group interactions and include only users who contributes posts, comments or likes into group activity. This approach corresponds to the original interactional intention of community concept [Rheingold, 1993; Fuchs, 2008] and allows us to avoid a bulk of accidental and inactive users.

The communication activity is distributed unequally among the group participants and *Table 1* shows statistics of the users contributions. We see that a minority of the core participants produces the majority of content and group activity.

Tab. 1. Group activity scores

Type of contribution	Share of users contribute 80% of communication units
Total sum of posts and comments = 42,671 Content contributors = 1,719 users	155 (9%) of all content contributors post 80% of all messages
Total likes = 67,897 Likes contributors = 4,849 users	136 (2.8%) of all likers contribute 80% of all likes
Likes receivers = 967	90 (9.3%) users who receive 80% of all likes

This result is consistent with previous research on online groups in general [Nielsen, 2006], and health-related groups in particular [van Mierlo, 2014; Carron-Arthur et al., 2014]. For instance, Chomutare et al. found very low user participation scores in general and high scores of activity only for few users [Chomutare et al., 2013; Mo & Coulson, 2010]. Leaders are the most active users who generates content and receives positive feedback because new content that meets group members' approval is the main drivers of the group's vitality and development.

The graph metrics of the friendship network are shown in *Table 2*. This community is composed of isolates (66.4%) and at least three sub-communities (one is the largest and densest and two are smaller and sparser, Fig. 2). Isolates are users who are not connected to any other users via friendship relations. User participation by content contribution is associated with inclusion in the giant network component (Chi-square = 214.109; df = 1; p-value < 0.000). It means 'likers' tend to be an atomized audience while members who contribute posts and comments tend to bond with each other and form a single connected network component.

Tab. 2. Graph metrics for 'friendship' network

Graph properties	Value (Share)
Nodes	5696
Edges	3967
Isolates	3726 (65.41%)
Connected components	148
Nodes in giant component	1634 (28.69%)
Edges in giant component	3775 (95.16%)
Modularity (with isolates) (Resolution 1.5)	0.634
Modularity (without isolates) (Resolution 1.5)	0.606
Density (without isolates)	0.002
Clusters in giant component	14
Mean geodesic distance	5.202
Diameter	15
Mean degree	1.393
Mean degree (without isolates)	4.027
Mean clustering coef.	0.241

We analyzed the relationship between user activity scores and friendship network centrality within the online group. We used a standard set of centrality measures (degree, betweenness and closeness [Freeman, 1978]) and added 'group involvement' which is the ratio of degree centrality to the total number of SNS member's friends (the personal network exposure rate) [Kwon et al., 2014].

Tab. 3. Relation between 'friendship' network centrality and communication activity of users

	Posts	Comments	Received 'likes'	'Likes'
Degree centrality[1]	0.588**	0.524**	0.605**	0.336**
Betweenness centrality[1]	0.449**	0.282**	0.347**	0.148**
Closeness centrality[1]	0.083**	0.085**	0.082**	0.066**
Group involvement[2]	0.198**	0.218**	0.243**	0.199**

[1] N = 5695
[2] N = 5419
** - Pearson correlation is significant at the 0.01 level (2-sides)

Table 3 highlights that there is a strong correlation between the number of the member's friends within the group (degree) and the number of likes they received. These findings demonstrate that activity and networking behavior correlate with each other in the AIDS-denialist community. Members who receive positive feedback (such as ' likes') become more central and tend to connect to each other forming a tight network component. This result is consistent with the results that Schweizer et al. received from an online-survey that "patients actively using online interaction services (posters) are more likely to have virtual relationships than patients only passively using them (lurkers)" [Schweizer et al., 2006]. *As a result, leadership in the online AIDS-denialists community is associated with high social network centrality and large number of friendship ties.* These pattern is consistent with the findings from previous research which suggests that core members could be identified as those who have the highest frequency of posts and network centrality [Gruzd & Haythornthwaite, 2013; Carron-Arthur et al., 2016].

But are these leaders and core members actual AIDS-denialists? To verify this we made a content analysis of posts and comments texts from the group's 'wall' to identify HIV-status and attitudes towards AIDS-denialism beliefs. We have coded these attributes only for 1,434 users because not all active members contribute by posting a text. The rest of the members just give 'likes', which is not enough to identify these attributes. The results of the text analysis show that 528 members are adherents of AIDS-denialism beliefs; 168 members posted sentences in favor of the medical 'orthodoxy'; 232 members expressed doubts toward both dissident and orthodox theories and chose neither of them; and 506 members posted nothing to reliably identify their HIV beliefs or attitude to ART treatment (in total 4768 with non-posters). We have mapped all these types of group members on the friendship network (Fig. 2). The graph visualization shows the largest cluster of cohesive and highly active members is the core of the AIDS-denialists.

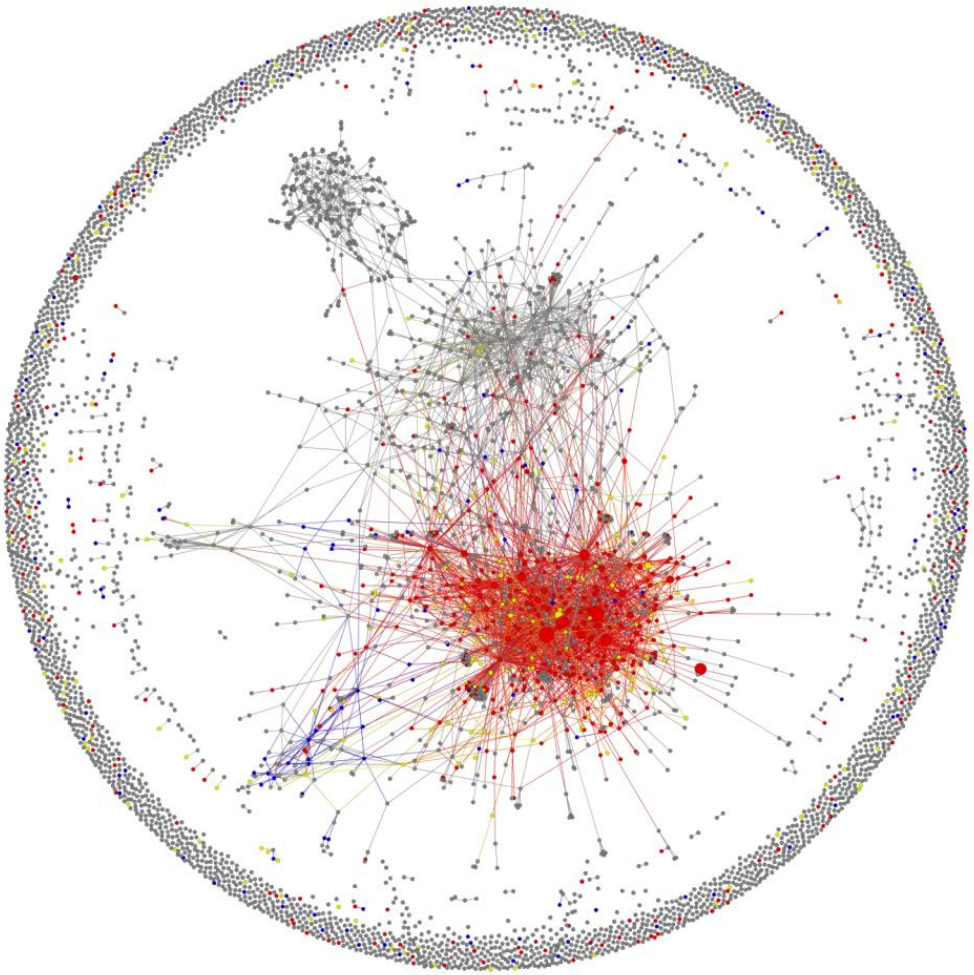

Fig. 1. Friendship network of group participants (red—AIDS-denialists; yellow—doubting members; blue—'orthodox' members; grey—unknown).

Finally, we ran a logistic regression to predict actual adherent AIDS-denialists within the group. The dichotomous dependent variable ‘AIDS-denialism beliefs’ was predicted through four kinds of user properties: participation activity (measured as posted messages, ‘likes’ and received feedback ‘likes’); friendship network centrality (measured as degree, betweenness and closeness centrality); inclusion into friendship network clusters (clusters were obtained by applying the Louvian community detection algorithm based on modularity optimization function [Blondel et al., 2008]); and available user meta-data as control variables (gender; total number of friends on SNS and HIV-status).

Tab. 4. Logistic Regression Model, Unstandardized Coefficients

	Dedication to AIDS-denialism beliefs		
Variables	Coefficient	Std. Error	z-value
Intercept (HIV-positive and female by default)	-1.510	0.172	-8.763 ***
Posts	0.232	0.041	5.659 ***
Comments	-0.025	0.004	-5.708 ***
Received likes	0.033	0.005	6.263 ***
Likes	-0.001	0.002	-0.356
Degree	-0.013	0.024	-0.532
Betweenness	0.00002	0.00001	1.491
Closeness	-0.156	0.124	-1.260
SNS 'friends'	-0.0002	0.0001	-1.630
HIV-negative	-0.209	0.360	-0.579
HIV-status unknown	-1.812	0.163	-11.138 ***
Cluster1	-11.400	835.100	-0.014
Cluster2	2.313	0.591	3.911 ***
Cluster3	2.447	0.634	3.858 ***
Cluster4	-11.460	648.700	-0.018
Cluster5	1.321	0.739	1.786
Cluster6	3.320	1.417	2.343 *
Cluster7	-11.400	725.000	-0.016
Cluster8	-11.570	650.600	-0.018
Cluster9	1.492	0.676	2.207 *
Cluster10	-11.190	838.400	-0.013
Cluster11	0.738	0.939	0.786
Cluster12	-1.507	1.310	-1.151
Cluster13	-11.440	402.400	-0.028
Cluster14	-11.520	839.600	-0.014
Gender (male)	0.259	0.116	2.227 *
Pseudo R2 (Nagelkerke)	0.381		

* p < .05 ** p < .01 *** p < .001

The model indicates that adherence to AIDS-denialism is positively and significantly related to the number of posts and received 'likes', which is consistent with high activity of community leaders. Surprisingly, the number of comments has a weak negative effect on adherence to AIDS-denialism, may be because deep involvement into discussions, which produces many comments indicates uncertainty. The strongest predictor for adherence to AIDS-denialism is user's belonging to particular friendship clusters (groupings), but different types of centrality in friendship network have no influence at all. Finally, male users are little bit more likely to be devoted AIDS-denialists than females. Thus, adherence to AIDS-denialism is associated mostly with high user participation activity and inclusion into special sub-

communities among group members. In general, this community structure is similar to other social networks found in health-related online groups [e.g. Cobb et al., 2010; Chomutare et al., 2013; Gruzd, & Haythornthwaite, 2013; Stewart, & Abidi, 2012].

Identifying the risk group potentially susceptible to becoming AIDS-denialists

For further analysis we defined the core of devoted AIDS-denialists as members who share AIDS-denialism beliefs and are connected by friendship relations with at least to another devoted member. This core counts 276 members. After we detected the core, we can identify a certain set of peripheral users who potentially are more likely to be affected by AIDS-denialist ideas – the risk group. The periphery is too large, full of accidental members and not sufficiently differentiated to effectively determine the risk group within it.

We used social contagion theory as a theoretical framework. According to A Dictionary of Psychology (3rd Ed.) social contagion is the spread of ideas, attitudes, or behavior patterns in a group through imitation and conformity [Oxford Reference]. From social contagion theory perspective, a direct interaction between an ordinary member and a core member bears the risk of the former being affected by the latter and starting to believe in AIDS-denialist ideas. Thus, in this study risk group was defined as peripheral members who contact and engage with core members through comments and especially 'likes'.

Studies comparing posters and lurkers in health-related self-help online groups (e.g. HIV/AIDS- and cancer-related groups) showed that posters scored significantly higher in receiving emotional and informational support compared to lurkers [Mo, & Coulson, 2010; Setoyama et al., 2011], which suggests that interacting members are potentially are more likely to be affected by AIDS-denialism beliefs in our case.

To investigate interaction among participants we consider the communication network based on the data on comments and 'likes' extracted from the group's wall and discussion boards. The communication network was built at the same time period as the friendship network but exceeds the latter by 1713 users because additional data was collected from discussion boards. New participants who post just on boards and not just on the 'wall' were added. Core AIDS-denialists that were determined in previous analysis were found within the communication network. The page of the group itself was also included in the network because there were messages posted on behalf of the group. The group page was assigned to the core because a team of moderators actually managing the group represents the AIDS-denialists beliefs and opinion. A few core members were not included in the communication network because they did not have

communication ties with non-core members, so the final number of core members in the communication network is 262.

Tab. 5. Graph metrics for communication (commenting and 'liking') network

Graph properties	Value (Share)	
	Full network	Core & final risk group network component (bipartite)
Nodes	7409	1600
Arcs	77850	16763
Unique arcs	26154	8004
Isolates	1381 (18.64%)	0
Connected components	5	1
Nodes in giant component	6018 (81.23%)	1600 (100%)
Arcs in giant component	26149 (99.98%)	8004 (100%)
Modularity (without isolates) (Resolution 1.5)	0.266	0.342
Density (without isolates)	0.001	0.003
Mean geodesic distance	3.419	3.866
Diameter	9	9
Mean degree (without isolates)	4.339	5.002
Mean weighted degree (without isolates)	12.915	10.477
Mean clustering coef.	0.135	-
Arcs statistics according to interaction type		
Intra-core arcs	32812 (42.14%)	0
Intra-core unique arcs	5344 (20.43%)	0
Mean intra-core arc weight	6.14	0
Intra-periphery arcs	8334 (10.71%)	0
Intra-periphery unique arcs	4678 (17.89%)	0
Mean intra-periphery arc weight	1.78	0
Core-periphery arcs	36704 (47.14%)	16763 (100%)
Periphery → core arcs	16958 (21.78%)	7128 (42.52%)
Core → periphery arcs	19746 (25.36%)	9635 (57.48%)
Core-periphery unique arcs	16132 (61.68%)	8004 (100%)
Periphery → core unique arcs	8560 (32.73%)	3635 (45.41%)
Core → periphery unique arcs	7572 (28.95%)	4369 (54.59%)
Mean Core-periphery arc weight	2.28	2.09

The highest relative frequency of interaction between core and periphery members (47.14% for core-periphery arcs; 61.81% for core-periphery unique arcs) indicates that

communication between core members and other group users and visitors plays very important role in group activity and development. However, communication inside the core is much more intensive than between the core and the periphery and much more intensive than communication inside the periphery (the mean weight of a communication tie inside the core is 6.14 as compared to 2.28 and 1.78 for core-periphery and periphery-periphery ties respectively). We suppose there is some sort of echo-chamber effect — AIDS-denialists comment and 'like' each other increasing the support of their own point of view.

To identify the risk group the network was transformed in the following way:

1) Only the core-periphery ties were considered. Internal ties for core members and for peripheral ones were excluded because these interactions were out of influence-adoption process.

2) The lower threshold was set for weighted degree among peripheral members to cut off members who had only accidental or weak interest in the group. This threshold is equal to 3 because the number of filtered users stopped to fall rapidly after this value. The remained network consists only of members who have one edge with a weight of 3.

3) The upper threshold was set for weighted degree among peripheral members to cut off members who are suspiciously heavily involved in interaction with the core. We allow that content analysis may have some accuracy errors in the belief identification, so some members may be wrongly attributed to periphery. High engagement with the core at least indicates a good awareness of AIDS-denialism theory and involvement in this discourse. 17 users (1%) from the top of peripheral members with highest weighted degree were cut off. We have cut off a share, not a number of users from the dataset because network properties such as weighted degree centrality have no growth limit due to the nature of its distribution (power law or lognormal [Clauset et al., 2009]).

The transformed network counts 1889 nodes (239 core members and 1650 members from the preliminary risk group (Figure 3). An import of members attributes, i.e. AIDS-denialism adherence, allows us to verify and clarify the composition of the actual risk group.

The preliminary risk group composition:

1. 181 members are adherents of AIDS-denialism beliefs (34,2% from all detected devoted AIDS-denialists). These participants were excluded from the risk group, as they already AIDS-denialists.
2. 100 members shared an 'orthodox' point of view (59,5% from all detected 'orthodox' members). These participants were excluded from the risk group, as they had stable views and even actually criticize and dispute dissident ideas in community discussions.

3. 185 members were doubting and undecided (79,7% from all detected doubting members). The highest percentages of doubting members in the risk group shows a high accuracy of network approach to identify a risk group of possible AIDS-denialism adopters. The doubting state of a member's mind indicates a logical connection between interaction and persuasion/influence effects.
4. 1184 members with unknown ADIS and medical beliefs. There were 314 members among them who were coded in content-analysis and that is 62% from all unknown members who appeared in the risk group.

The final risk group counts 1369 users (without dissidents and 'orthodox' members), who potentially are more likely to be affected by AIDS-denialism beliefs. Almost all members doubting ‘orthodox’ medical theory (79,7% from all doubting members) are in the risk group.

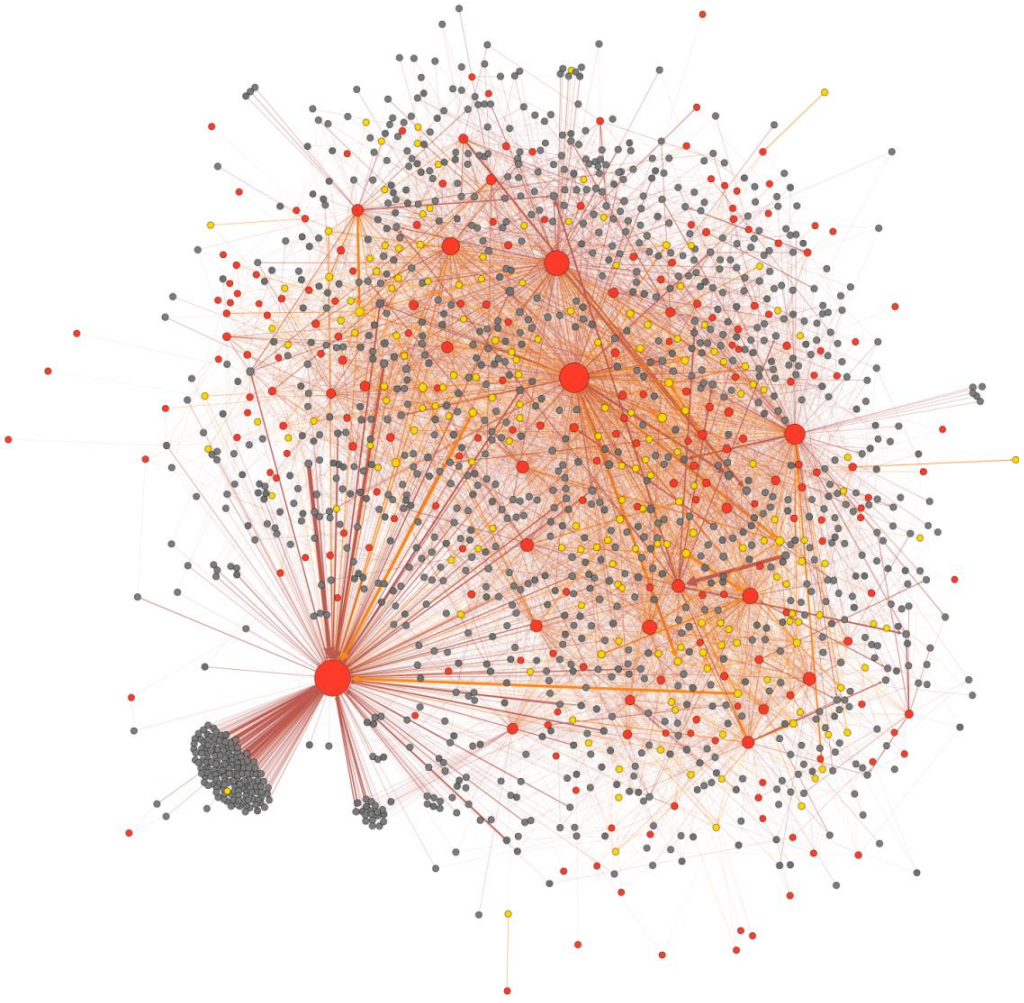

Fig. 2. Communication network between core members and the risk group (red — AIDS-denialists; yellow — doubting members; grey — unknown).

Discussion

Summary of Findings

This study investigated an AIDS-denialist online community on the Russian SNS *VK.com*. Using social network analysis combined with content-analysis we have identified the core of online community - cohesive and dedicated AIDS-denialists, and the risk group, which is not equal in composition to all peripheral members appeared in the online group. The risk group is the circle of users who engage with core members through online communication and may be more susceptible the AIDS-denialist propaganda. Analysis allowed to significantly reduce the target audience for possible intervention campaign and simultaneously increase the accuracy of user selection into the risk group (1369 users from the risk group is more than 10 times less than whole online group population counting over 15,000 users). Thus, online information interventions should be aimed at this risk group audience in the first place to prevent their adoption of AIDS-denialism beliefs, further spread of AIDS-denialism, and pernicious health consequences associated with being an HIV-positive AIDS-denialist.

More research on influence of AIDS-denialism on HIV-positive online group members is needed. Of particular interest are longitudinal or case control studies that could detect the size of effect of AIDS-denialist propaganda that is communicated from hard-core denialists to the risk group, different factors associated with higher or lower susceptibility to AIDS-denialist views, and real health behavior change that occurs with becoming an AIDS-denialist.

Limitations

The approach we follow in community definition considering only posters and likers as group's members has some limitations, and the most important is that 'lurkers' and passive audience of group subscribers are not included into research focus. They may possibly be affected by the group's content and would adopt AIDS-denialism ideas without a direct interaction with group members. Another limitation is that we analyze only publically available data on user interaction and did not take into account private messages exchanged between them, which are inaccessible due to technical and ethical reasons. However this data may provide additional information on users' relations, attitudes and opinions. The last big limitation of this study is that we do not have data on real health behavior of group members and therefore cannot observe particular changes in their behavior under the community influence.

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Yuri G. Rykov
National Research University Higher School of Economics, St. Petersburg School of Social Sciences and Humanities, The Laboratory for Internet Studies;
E-mail: yrykov@hse.ru