

Network Structure of an AIDS-denialist Online Community: Identifying Core Members and the Risk Group

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Abstract

With rapid growth of online social network sites, the issue of health-related online communities and its social and behavioral implications has become increasingly important for public health. Unfortunately, online communities often become vehicles for promotion of pernicious misinformation, in particular, that HIV-virus is a myth (AIDS-denialism). This study seeks to explore online users' behavior and interactions within AIDS-denialists community to identify and estimate the number of those, who potentially are most susceptible to AIDS-denialists arguments - "the risk group" in terms of becoming AIDS-denialists. Social network analysis was used for examining the most numerous AIDS-denialist community (over 15,000 members) in the most popular Russian SNS "VK.com". In addition, content-analysis was used for collecting data on attitudes towards AIDS-denialists arguments and participants' self-disclosed HIV-status. Two datasets were collected to analyze friendship ties and communication interactions among community members. We have identified the core of online community - cohesive and dedicated AIDS-denialists, and the risk group: users who communicate with core members, and, thus, can be more susceptible to the AIDS-denialist propaganda and their health behaviours (e.g. refusing treatment). Analysis allowed to significantly reduce the target audience for possible intervention campaigns and simultaneously increase the accuracy of determining the risk group composition.

Keywords: health-related online community, HIV/AIDS, social networks analysis, social contagion, risk group

Introduction

With rapid growth of online social network sites (SNS), the issue of health-related online communities and its social and behavioral implications has become increasingly important for public health and healthcare (Centola, 2013). Such research focuses not only on positive outcomes of online groups use such as strong emotional support (Chung, 2014) but also on cases

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of misinformation and pernicious health practices spreading via the Internet and SNS such as well-known anti-vaccination or pro-anorexia movements (Yom-Tov, & boyd, 2014).

This work continues and complements the previous study of the AIDS-denialists online community in Russian SNS “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 online community 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 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 online communities and on those group members, who doubt the HIV science (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 of the AIDS-denialists online community from quantitative perspective to identify and estimate those, who potentially are most susceptible to AIDS-denialists arguments - “the risk group” in terms of becoming AIDS-denialists.

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 (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 interventions that are directed against AIDS-denialism on SNS.

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, etc. There are several types of online health communities. The most frequent one is online support and patient self-help groups (Bar-Lev,

2008; Coursaris, & Liu, 2009; Mo, & Coulson, 2008; Setoyama et al., 2011; Shi, & Chen, 2014). Healthcare professionals as well as patients become members of online communities prompting 'doctor - patient' communication (Santana et al, 2010) or professional knowledge sharing (Stewart, & Abidi, 2012). 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 of these communities mostly focuses on relationship between online users' behavior, coping behavior and health outcomes depending on characteristics of participants, interaction and content.

There are numerous studies that use social network analysis (SNA) to explore community structure and interaction among participants in online health-related groups such as smoking cessation communities (Cobb et al., 2010), diabetes forums (Chomutare et al., 2013), healthcare (Gruzd, & Haythornthwaite, 2013) or cancer-related groups (Himmelboim, & Han, 2013) on Twitter. Cobb et al (2010) 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 the increased likelihood of not smoking. Thus, smoking cessation behavior is associated with higher engagement with members of the online forum. Gruzd and Haythornthwaite (2013) found that the community is sustained by “a strong core of active participants..., who lead in posting and prominence in the network”. Also they showed that attention-giving from the core to other group members sustains the community vitality. Meanwhile, Chomutare et al. (2013) discovered that the most central and influential members are often patients who were more experienced in coping with the disease (with more years-since-diagnosis). It means that a few experts become an authority in the online community and act as mentors for the majority of newcomers and newly diagnosed patients. Additionally, Himmelboim and Han (2013) found that healthcare providers and institutions are not the main sources of health information and did not enable formation of dense and sustained communities.

Thus, network analysis of social ties and interactions within online health-related communities is used to identify leaders, explore influence, and understand interrelation between characteristics of online user behavior and some health conditions.

Spread of behavior and social contagion on networks

Another research direction in the domain of health behavior is the studies of epidemics and behavior diffusion through social networks (Smith & Christakis, 2008). Behavioral phenomena such as 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 (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 such health-related behaviors as obesity (Christakis & Fowler, 2007), smoking (Christakis & Fowler, 2008), drug use (Mednick et al., 2010) or alcohol consumption (Rosenquist et al., 2010) through networks.

Several studies report that online health information-seeking behavior is associated with better awareness for treatment decisions, increased patient satisfaction and better medical outcomes in general (Longo et al., 2010; Siliquini et al., 2011; Jamal et al., 2015). We assume that partaking in online health-related community may affect actual health behavior greater than just online health information-seeking because social contacts strengthen information perception. Participation in HIV/AIDS online communities provides an access to others who have similar experience and it may result in 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 to adopt AIDS-denialist views. Adherence to AIDS-denialists beliefs is not just a cognitive aspect of individuals but it may cause further changes in actual health behaviour, such as lack of condom use (Bogart, & Bird, 2003), refusing HIV testing (Bohnert, & Latkin 2009) and antiretroviral treatment (Kalichman et al., 2010; Bogart et al., 2011). Social contagion can be a mechanism of influence of AIDS-denialist beliefs; there is evidence of similar possibility of being influenced by these beliefs that is based on studied outcomes of online health communities (Murthy et al., 2011; Myneni et al., 2016). Thus, engaging into an online AIDS-denialist community through interaction with its core members raises a risk of being affected by these beliefs and of negative health outcomes.

Research Questions

Studies of online communities have shown that a small group of users may have a significant influence on other members. Identification of these users is helpful for understating functioning of a community (Tang, & Yang, 2010) and can be useful in reaching different public health policy goals (Zhao et al., 2014). Specifically for an AIDS-denialists online community detection of core members means identification of the source of influence in the group.

RQ1: What is the structure of the AIDS-denialists community? Is there a cohesive core of devoted AIDS-denialists or are members separated 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 (Nattrass, 2013). However, leaders detection helps to determine which community members may be affected by them. The analysis of 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 propaganda.

RQ2: 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 of AIDS-denialists on the most popular Russian SNS “VK.com”, which is open for everybody who is willing to join. By the end of the study this group amounted to about 15,000 members. The group page consists of a short description section with the mission and rules; members list; the main message board called 'the wall'; discussion boards for specific topics and sections for videos, audios and references. Besides joining the group, users may post, comment and like the group content and add each other to their 'friend lists'. The data on users' activity and 'friendship' relations are in open access. This research deals only with the data publically available from the SNS server. The data was collected automatically using application programming interface software specially designed for this project.

We define user's belonging to the online community through participation in the group's activity and consider only users who left posts, comments or likes in the group. This approach follows the interactional intention of community concept (Rheingold, 1993; Fuchs, 2008) and allows us to avoid a bulk of inactive users. Two datasets were collected to analyze 'friendship' and communication relations. The 'friendship' network dataset includes: 1) the data from the

group's 'wall' with users' activity scores and the content (starting from the date of the earliest post, December 2, 2008 and until January 20, 2015); 2) the metadata of all users (gender, age, location, etc.); 3) the data on 'friendship' relations among the users. The communication network dataset additionally includes: 1) the data from discussion boards on the users' posting activity; 2) the data on communicative relations among the users: 'likes', comments and mentionings. Both datasets were filtered by excluding deleted or banned user profiles.

Content-analysis

According to Hsieh and Shannon (2005), there are three main approaches of qualitative content-analysis that are widely applied in health studies: conventional, directed, and summative. An approach used in our study is closer to the summative content-analysis, which is usually applied for understanding the context of content usage. We analyzed posts and comments to identify users' attributes relevant for our study: HIV-status and attitude towards AIDS-denialism beliefs. As a result, we have received a descriptive summary of users' utterances and sentiments on related issues.

The HIV-status attribute could be positive, negative or unknown/closed. Positive or negative HIV-status was assigned to user if we found direct information on the status, such as a reference to HIV test results, number of years since HIV diagnosis or HIV treatment experience, as, for example, the following post demonstrates:

I got “+” on the tenth week of my pregnancy.

Attitudes towards AIDS-denialism were split into 4 sentiment groups: 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 could not be determined by the analysis ('unknowns'). Adherence to AIDS-denialism was assigned if a 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 of any nuances that are 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.

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

‘Doubting’ category was assigned to a user, if he/she directly claimed that he/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:

Citizens, so answer me, the illiterate, the question - to continue taking pills or to stop?

‘Orthodox’ category was assigned to a user, if he/she expressed statements in favor of the official medicine theory or against the group’s beliefs, for instance, demonstrated a positive attitude regarding HIV treatment:

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

Network Analysis

First, we analyzed the ‘friendship’ network. Nodes in the network are users participating in the online group. Ties are mutual ‘friend’ relationships between them. The analysis of network characteristics was combined with personal activity scores and personal attributes extracted from content-analysis to identify the community’s core. We examined how status of a dissident is connected to user behavior within the group. ‘Friendships’ network is important because it reflects the informal social structure of a group, its cohesion and clustering. From an individual perspective ‘friendships’ relations also reflect some kind of trust and amount of intragroup social capital (Ellison et al., 2011; Ellison, & boyd, 2013).

Second, we analyzed the communication network between core and peripheral members to identify the risk group. Ties appear when one member comments on or likes a post (or a comment) left by another, or when one member mentions another in his post. Thus, communication network is directed and weighted. Gephi and R software were used for network and statistical analysis.

Results

Identifying the community core of AIDS-denialists

We consider leaders as the most active users who generate content and receive positive feedback because new and socially approved content is the main contribution into the group’s

vitality and development. *Table 1* shows that the communication activity is distributed unequally among the group participants: a minority of users produces the majority of group activity. This result is consistent with previous research on online groups in general (Nielsen, 2006), and health-related groups in particular (Mo, & Coulson, 2010; Chomutare et al., 2013; van Mierlo, 2014; Carron-Arthur et al., 2014).

Table 1. Group activity scores.

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

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 (Fig. 1). Isolates are users who are not connected to anyone 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 content contributors tend to bond with each other and form a single connected component.

Table 2. Graph metrics for 'friendship' network.

Graph metrics	
Nodes	5695
Edges	3967
Isolates	3725 (65.41%)
Connected components	148
Nodes in giant component	1634 (28.69%)
Edges in giant component	3775 (95.16%)
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's activity scores and 'friendship' network centrality within the online group. We used the 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' (Kwon et al., 2014). Also we added duration of user membership per days since the date of the first post in the group to control these correlations.

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

	Posts	Comments	Received likes	Likes	Duration ³
Degree ¹	0.588*	0.524*	0.605*	0.336*	0.038
Betweenness ¹	0.449*	0.282*	0.347*	0.148*	0.054*
Closeness ¹	0.083*	0.085*	0.082*	0.066*	-0.025
Group involvement ²	0.198*	0.218*	0.243*	0.199*	-0.119* ⁴
Duration ³	0.161*	0.019	0.025	0.003	1

¹ N = 5695; ² N = 5419; ³ N = 1719; ⁴ N = 1571

* - Pearson correlation is significant at the 0.01 level (2-sides)

Table 3 shows that activity and networking behavior are positively correlated in the AIDS-denialist community. The strongest correlation is between the number of the users' 'friends' within the group (degree) and the number of received likes, so members who receive more positive feedback are more central. Thus, leadership in the online AIDS-denialists community is associated with a larger number of 'friendship' ties. This result is consistent with previous findings, which suggests that leaders could be identified as those, who have the highest frequency of posts and the highest network centrality (Schweizer et al., 2006; Stewart, & Abidi, 2012; Gruzd, & Haythornthwaite, 2013; Carron-Arthur et al., 2016).

But are these leaders actual AIDS-denialists? To verify this, we conducted a content-analysis of posts and comments to identify HIV-status and attitudes towards AIDS-denialism beliefs. We analyzed only 1,434 users because not all members contribute by posting a text. The rest of the members just give 'likes', which is not enough to identify these attributes. It was found that 528 members were 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; 506 members posted nothing to reliably identify their HIV beliefs (the constitute 4,768 users together with non-posters). We mapped members’ attitudes on the ‘friendship’ network graph (*Fig. 1*). It shows the largest cluster of cohesive and highly active members is the core of the AIDS-denialists.

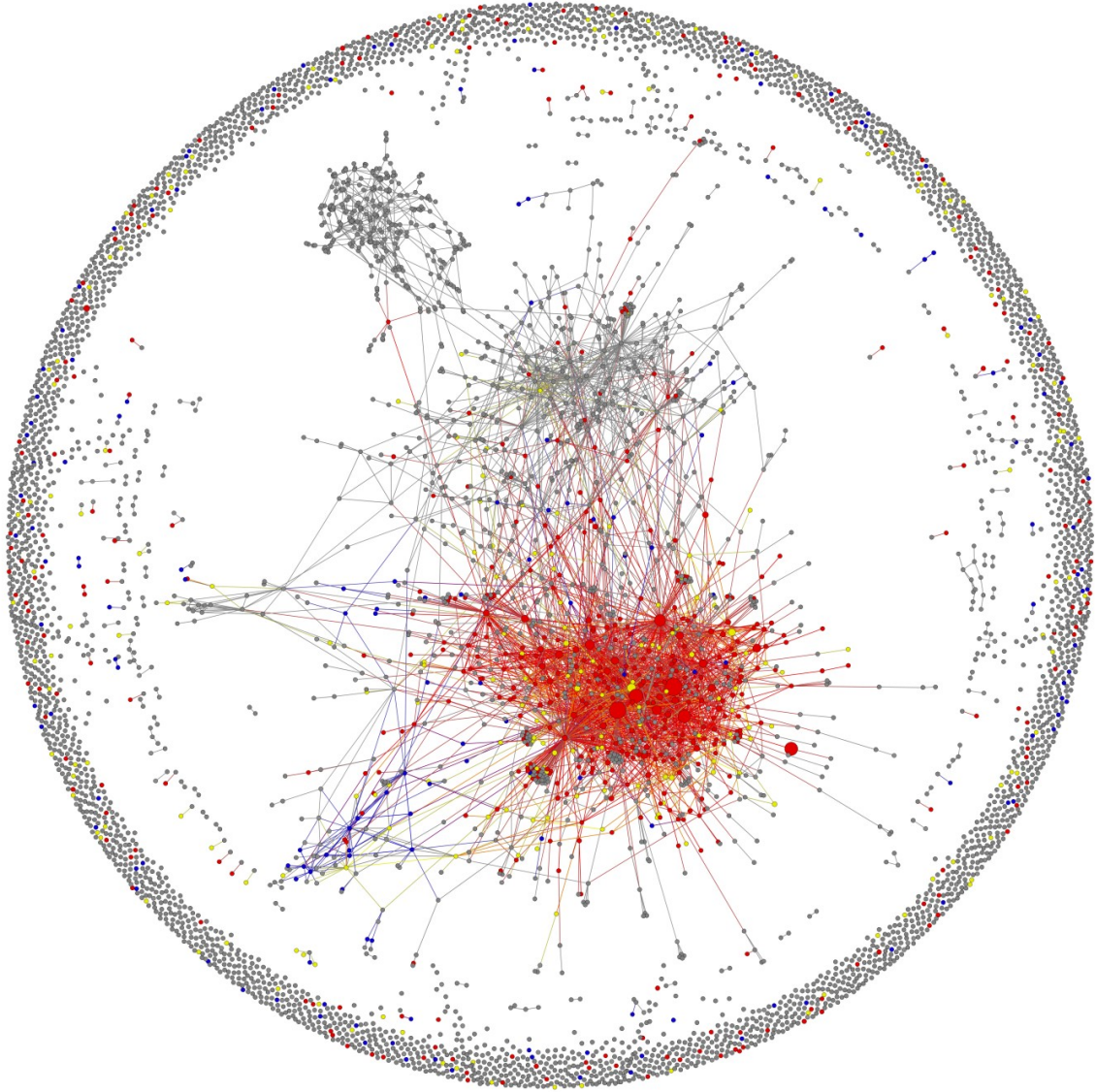


Figure 1. ‘Friendship’ network of group participants (red—AIDS-denialists; yellow—doubting members; blue—‘orthodox’ members; grey—unknown; larger vertex size = higher activity).

Finally, we ran a logistic regression to test relationships between adherence to AIDS-denialism and online behaviors within the group. Four kinds of user properties were used: activity (measured as the number of posted messages, ‘likes’ and received feedback ‘likes’);

‘friendship’ network centrality (measured as degree, betweenness and closeness centralities); inclusion into ‘friendship’ network clusters (clusters were obtained by applying the Louvain algorithm (Blondel et al., 2008)); and available user’s meta-data as control variables (gender; total number of friends on SNS and HIV-status).

Table 4. Logistic Regression Model, Unstandardized Coefficients.

	Adherence to AIDS-denialism beliefs	
	Coefficient	Std. Error
<i>Intercept (HIV-positive and female)</i>	-1.510 ***	0.172
Posts	0.232 ***	0.041
Comments	-0.025 ***	0.004
Received likes	0.033 ***	0.005
Likes	-0.001	0.002
Degree	-0.013	0.024
Betweenness	0.00002	0.00001
Closeness	-0.156	0.124
SNS 'friends'	-0.0002	0.0001
HIV-negative	-0.209	0.360
HIV-status unknown	-1.812 ***	0.163
Cluster89	-11.400	835.100
Cluster114	2.313 ***	0.591
Cluster447	2.447 ***	0.634
Cluster879	-11.460	648.700
Cluster894	1.321	0.739
Cluster954	3.320 *	1.417
Cluster1073	-11.400	725.000
Cluster1169	-11.570	650.600
Cluster1188	1.492 *	0.676
Cluster1541	-11.190	838.400
Cluster2595	0.738	0.939
Cluster2666	-1.507	1.310
Cluster3324	-11.440	402.400
Cluster3786	-11.520	839.600
Gender (male)	0.259 *	0.116
Pseudo R ² (Nagelkerke)	0.381	
N = 5695		
* 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 group

leaders. Somewhat surprisingly, the number of comments has a weak negative effect on adherence to AIDS-denialism; this may mean that a large number of comments indicates the user's uncertainty. User's inclusiveness into certain 'friendship' network clusters shows the strongest effect in the model, but different types of centrality have no effect at all. Finally, male users are a slightly more likely to be dedicated AIDS-denialists than females. Thus, adherence to AIDS-denialism is associated mostly with high user online activity and inclusiveness into some community clusters. 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 dedicated AIDS-denialists as members who share AIDS-denialism beliefs and are connected by 'friendship' relations with at least one other dedicated member. This core amounts to 276 users. Further, we can identify a certain set of users who are more likely to be affected by them - the risk group. The periphery is too large, full of accidental users and not sufficiently differentiated to effectively determine the risk group within it.

We used social contagion theory as a theoretical framework. According to “Dictionary of Psychology” social contagion is the spread of ideas, attitudes, or behavior patterns in a group through imitation and conformity (Colman, 2008). According to the social contagion theory, a direct interaction between an ordinary member and a core member bears the risk of the former being affected and adopting AIDS-denialist ideas. Thus, in this study risk group was defined as a set of peripheral members who engage with core members through comments and especially through ‘likes’.

Studies comparing posters and lurkers in online health-related self-help groups showed posters scored significantly higher in receiving emotional and informational support compared to lurkers (Mo, & Coulson, 2010; Setoyama et al., 2011). Likewise, Chen and Shi (2015) reported that informational and emotional support increases with a greater intensity of communication in HIV/AIDS online group. Thus, the members with the greater intensity of interactions are more exposed to be affected by AIDS-denialism beliefs in our case.

The graph metrics of communication network are shown in the *Table 5*.

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

Graph metrics	Full network	'Core & risk group' 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

Core AIDS-denialists who were determined in previous analysis were found within the communication network. The page of the group itself was included in the network and assigned to the core. The highest relative frequency of interaction (*Table 5*) indicates that communication between core members and other users plays an important role in group activity. However, communication inside the core is much more intensive than core-periphery communication and

all the more than among periphery. We suppose there is some sort of echo-chamber effect — AIDS-denialists comment and ‘like’ each other reinforcing the support of their beliefs.

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

1. Only the core-periphery ties were considered.
2. The lower and upper thresholds were set for weighted degree among peripheral members to cut off accidental members and members who are suspiciously heavily involved in interaction with the core (high engagement with the core at least indicates a good awareness of AIDS-denialism tenets). The lower threshold for weighted degree was 3. As an upper threshold 1% of peripheral members with highest weighted degree were cut off. A share of users were cut off because network properties such as weighted degree have no growth limit (Clauset et al., 2009).

The transformed network contains 1,889 nodes and the preliminary risk group — 1,650. Adherence to AIDS-denialism determined through content-analysis allows us to verify and clarify the composition of the actual risk group.

The preliminary risk group composition:

1. 181 members were adherent AIDS-denialists (34.2% from all dedicated AIDS-denialists).
2. 100 members shared ‘orthodox’ beliefs (59.5% from all detected 'orthodox' members).
3. 185 members were doubting and undecided (79.7% from all doubting members). The highest proportion of doubting members in the risk group shows a high accuracy of network approach based on the social contagion theory to identify a risk group of possible AIDS-denialism adopters.
4. Beliefs of 1,184 members remain unknown. There were 314 users among them, who were coded in content-analysis and that is 62% from all unknown members who appeared in the risk group.

Dedicated AIDS-denialists and ‘orthodox’ users were excluded from the final risk group, as the first are already AIDS-denialists, and the second have stable pro-science views and even criticize dissidents. Thus, the final risk group counts 1,369 users and almost all doubting members (79.7% from all) appear in the risk group (Fig. 2).

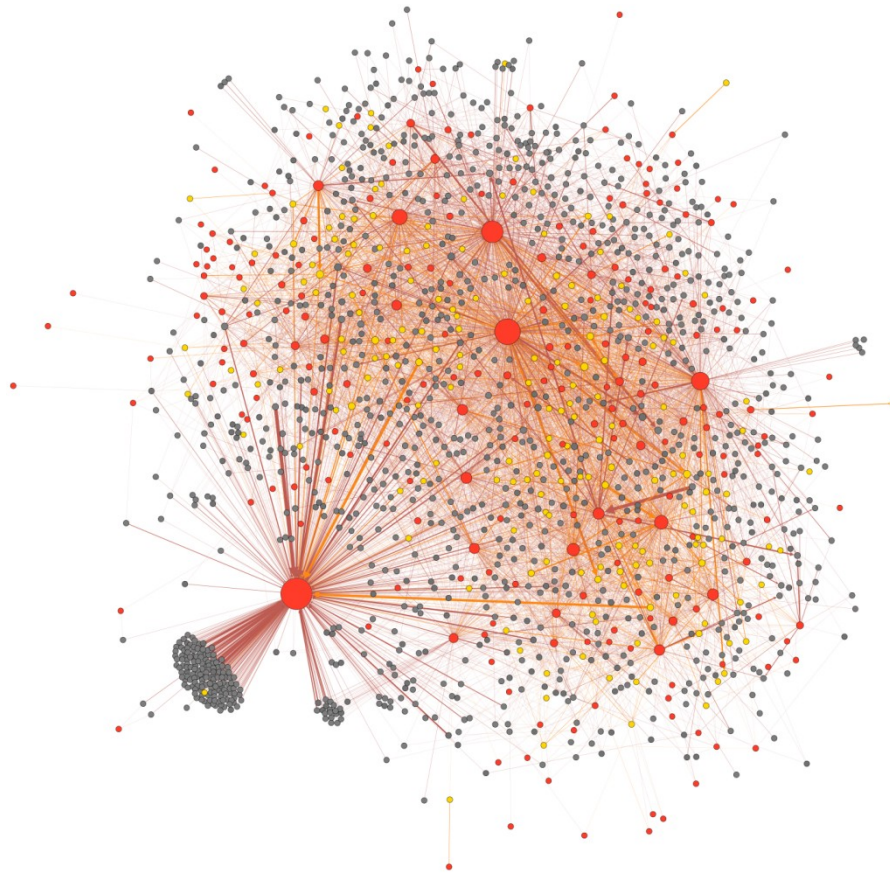


Figure 2. Communication network between the core members and the final risk group (red—AIDS-denialists; yellow—doubting members; grey—unknown; larger vertex size = higher activity).

Discussion

Summary of Findings

This study investigated the AIDS-denialist online community on the leading Russian SNS. Using SNA combined with content-analysis we have identified the core of online community - a cohesive set of devoted AIDS-denialists, and the risk group, which is not equal to all peripheral members appearing in the online group. The risk group is a set of users who engage with core members through online communication and may be more susceptible to the AIDS-denialist propaganda. The analysis allowed us to significantly reduce the target audience for possible intervention campaigns and simultaneously increase the accuracy of the risk group composition (1,369 users from the risk group is more than 10 times less than the entire online group population counting over 15,000 users).

Risk group and potential health behavior outcomes

As online health information-seeking behavior is one of the sources for illness representation, it leads to changes in illness cognition (Hagger, & Orbell, 2003) and usually positive changes in medical outcomes (Longo et al., 2010; Siliquini et al., 2011; Jamal et al., 2015). Partaking in online health-related community may affect actual health behavior greater than just online health information-seeking because social contacts strengthen the effect on illness representation or coping motivation of a patient (Cobb et al., 2010). Therefore, partaking in harmful health-related online communities raises a risk of misinformation, adverse changes in coping behavior and negative health outcomes. The available data (Meylakhs et al., 2014) indicates that interactions with core AIDS-denialists in the online community raises and enhances doubts of some newcomers about standard illness representation - causes, consequences, timeline, identity and controllability of HIV/AIDS. Being a part of the risk group that we have identified in our study means to be more exposed to the patterns of AIDS-denialists coping behavior. Individuals from the risk group may follow some of such patterns: refuse HIV testing and antiretroviral treatment, stop visiting AIDS-centers and stop tracing medical indicators (Bogart, & Bird, 2003; Bohnert, & Latkin, 2009; Kalichman et al., 2010; Bogart et al., 2011). Thus, information interventions are needed to prevent their adoption of AIDS-denialism and its further spread.

More research on influence of AIDS-denialism on HIV-positive online group members is needed. Of particular interest are longitudinal and case control studies that could detect the size of the 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 changes that occur after having become an AIDS-denialist.

Limitations

The approach we use in community definition, considering posters and likers only as group's members has some limitations, the most important being that 'lurkers' and passive audience of group subscribers are excluded from the research focus. They can possibly be affected by the group's content and adopt AIDS-denialism ideas without direct interactions with group members. Another limitation is that we analyze only publically available data on users interactions and exclude private messages exchanged between them, which are inaccessible due to technical and ethical reasons. Another limitation of this study is that we do not have data on real health behaviors of group members and, therefore, cannot observe specific changes in their

coping behaviors and health outcomes occurring under the community's influence. Furthermore, we do not have data on personal biographies and the context of participation such as coming to the online community before or after the diagnosis which may influence user's perception of and attitude to AIDS-denialism. Finally, a methodological limitation is that the community detection algorithm used in the study does not identify overlapping communities in the friendship network.

Acknowledgements

The study received funding from the projects "Internet Use and Internet Users: Cross-country and Cross-regional Comparisons" in 2016 and "Health Economics: Developing Practical Tools for Making of Decisions in Healthcare" in 2017, both carried out within the framework of the Basic Research Program at the National Research University Higher School of Economics (HSE). The empirical data were collected by using the "VKGroups" and the "VKContentNet" software developed in the "Center for Sociological and Internet Research," Saint Petersburg State University. An earlier version of this article was presented at the 2016 International Conference on Social Media & Society.

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