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Suicide-Related Groups and School Shooting Fan Communities on Social Media: A Network Analysis

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Abstract: As network structure of virtual communities related to suicide and school shooting still remains unaddressed in scientific literature, we employed basic demographics analysis and social network analysis (SNA) to show common features, as well as distinct facets in the communities' structure and their followers' network. Open and publicly accessible data of over 16,000 user accounts were collected with a social media monitoring system. Results showed that adolescents and young adults were the main audience of suicide-related and school shooting fan communities. List of blocked virtual groups related to school shooting was more extensive than that of suicide, which indicates a high radicalization degree of school shooting virtual groups. The homogeneity of followers' interests was more typical for subscribers of suicide-related communities. A social network analysis showed that followers of school shooting virtual groups were closely interconnected with their peers, and their network was monolithic, while followers of suicide-related virtual groups were fragmented into numerous communities, so presence of a giant connected component in their network can be questioned. We consider our results highly relevant for better understanding the network aspects of virtual information existence, harmful information spreading, and its potential impact on society.

Keywords: network analysis; social network analysis; online behavior; virtual groups; virtual communities; suicide; school shooting; social media

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1. Introduction

Virtual communities are usually investigated in a very broad context, including information modeling [1–3], social and political psychology [4–6], population research [7,8], and gender studies [9,10]. However, there are no works so far that examine a network structure of virtual groups publishing harmful content (i.e., inciting to a violent behavior, self-harm, or suicide). The reason is that the term "harmful" comprises any information related to all kinds of harms and deviations, from those promoting anorexia and adult content to politically charged "hate groups" [11–15].

Previous studies of online school shooting communities have almost exclusively focused on media coverage of school shooting acts, narratives of mass violence, or the global school shooting subculture [16–19]. Subgroups of users involved in such communities were classified and analyzed with the online ethnography method [20–22]. A number of studies have examined dynamics of feedback observed in social networks in response to school shooting acts, including the "copycat effect" [23,24]. Other works have explored methodology for search and analysis of harmful content on Facebook, LiveJournal, and YouTube [25,26]. In addition, some of our previous studies [27,28] have provided brief overviews of demographic characteristics of school shooting communities' members. However, the network structure of online groups related to school shootings remains almost unaddressed in the scientific literature.

Virtual communities related to depression and suicide were investigated to understand the impact of social media on behavior of users who consumed harmful information on the web [29–33]. Online content and online communication related to suicide, as well as possible transformation of social media into a digital tool for psychological support and suicide prevention, were also considered [34–37]. Moreover, there are an extremely limited number of papers that have reported social network analysis to investigate virtual suicide-related communities [38].

The aim of our study was to analyze and compare virtual communities of two types: related to school shooting and suicide. The employed comparison criteria included (a) demographic profile of communities' members (sex, age, and geographical location) and (b) community network parameters, internal integrity of their structures, and possible interconnection between their members. For the latter, five communities of each type were analyzed.

2. Materials and Methods

This research was fully based on publicly available and anonymized user data from the largest European social networking site vk.com, https://vk.com (accessed on 22 January 2024). Social media monitoring system (the InfoWatch Kribrum) was used for collecting social and demographic data. When one of virtual groups related to school shooting was detected, it was used as a reference community. Then, by applying the snowball sampling method, four more communities related to school shooting were identified. Likewise, five communities related to suicide were identified. The search employed the following criteria: (a) presence of explicit linguistic markers and visual markers of the Columbine subculture/suicide; (b) number of followers from 100 to 10,000 users. Finally, a list of 10 virtual communities were constructed for further analysis (Table 1).

Table 1. Virtual communities analyzed.

Community ID	Community Name	Followers, n	Community Type
1	Ask True Crime Community (ATCC)	167	School shooting
2	I love irina yarovaya	130	School shooting
3	Chapel of Skorm	21	School shooting
4	Daniil Zasorin//Bullying. Bullying at school	98	School shooting
5	Group in memory of Vlad	89	School shooting
6	i hate myself and want to die	255	Suicide
7	RARE SUICIDE	6804	Suicide
8	This world is eating me up inside	5518	Suicide
9	Suicide today	3013	Suicide
10	Notes of a suicider	295	Suicide
Followers, total		16,390	n/a

The data analysis consisted of four stages:

(1) Construction communities' demographic profile.
(2) Estimation the proportion of active and blocked users in communities of both types and how a number of blocked accounts corresponded to a communities' content as it reflects community radicalization degree.
(3) Subscriptions analysis to estimate the homogeneity of followers' interests.
(4) Analysis and visualization of the communities' network structure.

Analysis at the fourth stage was conducted with social network analysis techniques (SNA). Networks and graphs were constructed and visualized with Gephi software, version 0.9.3.

3. Results

3.1. Basic Characteristics of the Communities and Their Followers

In total, anonymized data of 16,390 user accounts were collected, including 505 (3%) of school shooting communities' followers and 15,885 (97%) of suicide-related communities' followers. Additionally, 4223 (25.8%) accounts were private and did not provide an access to their profile information or friend list; therefore, they were excluded from the study dataset and analysis.

3.1.1. Sex and Age

In all communities, the ratio of females to males was rather even and comprised 52.5% females to 47.5% males. Yet, in some groups, sex ratio imbalances were observed; for example, members of the school shooting fan community 3 were mostly males (85.7%) and females were the majority (71.4%) of the suicide-related community 6.

Such an imbalance is explained by community content. Community 3 contained severely depressive, partially aggressive, and even satanistic content combined with some visual markers of the Columbine subculture; for example, a short looped video with Harris and Klebold walking with the "natural selection" lettering in background. This community was also the smallest one and many of its members likely belong to a close circle of people acquainted with a group creator. Community 6 was also a small group administered by a girl. Most of the community posts reflected a feminine perspective on depression.

In total, 69% of users did not specify their age. Available data showed that age subgroups of the communities' members consisted of 11.7% users less than 18 years old, whereas 11.6% were between 19–22 years old, 3.3% were between 23–26 years old, 1.8% were between 27–30 years old, and 2.6% were over 30 years old.

3.1.2. Followers' Geography

Data on users' geographical locations were rather limited: 40.7% of communities' followers did not specify their country of residence. The information provided by other followers showed that they resided in Russia (34.6%), Ukraine (10.1%), US (2.7%), Japan (1.8%), Kazakhstan (1.6%), Belarus (1.6%), and Germany (1.3%). Other countries of residence comprised less than 1% of school shooting and suicide-related communities' audience.

It is worth mentioning that 84 followers specified "cemetery" as their city of residence and 30 followers indicated Littleton, the city of the Columbine tragedy.

In addition, the lowest anonymity threshold was observed in community 9. Only 36.4% of its followers closed the information on their residence, whereas, in other communities, they exceeded 50%. Community 9 positioned itself as a platform for sharing music of a local rap band. Despite the disclaimer claimed that the community had nothing to do with suicides, its content was full of suicide stories.

3.1.3. Blocked Accounts

In total, 85.3% of all investigated accounts in the network segment were active, whereas 5.9% were blocked and 8.8% were deleted. The largest share of blocked accounts belonged to followers of school shooting community 4 (30.6%), school shooting community 2 (28.5%), and school shooting community 1 (12.6%). The largest number of deleted accounts was also found in school shooting community 1 (16.8%) and community 3 (9.5%).

The content of these communities reflects pseudo rejection of the school shooting issue, games with followers who invited to "talk" virtually with killers and mass shooters, or sarcastic criticism of authorities, individual officials, and experts engaged in legal and ideological opposition to school shooting.

Among suicide-related communities, community 8 had the largest number of deleted (10.3%) and blocked (5.8%) accounts.

3.1.4. Shared Subscriptions

Followers of the communities related to suicide had 224,904 shared subscriptions to other virtual groups dedicated to depression, suicide, and weapons, self-harm, and behavioral deviations. To investigate the extent to what followers of these groups were involved in consumption of a destructive online content, we collected data on the blocked communities they followed. The final list of shared but blocked communities included several groups dedicated to drugs, death, suicide, depression, and murders.

Followers of the school shooting communities had 42,446 common subscriptions to virtual groups dedicated to criminals, killers, behavioral deviations, depression, and suicide. We also identified at least 58 shared but blocked communities dedicated to Columbine, which obviously indicated that followers of school shooting communities actively migrated from one group to another if a community they followed got blocked.

To investigate the homogeneity of the followers' interests, we compared how many followers of the suicide-related communities were subscribers to the school shooting communities and vice versa. Results indicated that followers of suicide-related communities were mainly subscribed to suicide-related virtual groups; for example, community 8 and community 7 united the largest number (2956) of other suicide-related communities' subscribers in our dataset. In contrast, there were followers of virtual school shooting communities who subscribed not only to school shooting online groups but suicide-related either.

In summary, followers of school shooting communities expressed an interest in suicide-related online groups, whereas followers of suicide groups were not interested in school shooting content.

3.2. Network Characteristics and Graphs

Next, we conducted SNA of the considered suicide-related and school shooting virtual communities. We based our analysis on concepts defined as:

- Node is a user in a graph of a social network community.
- Isolated node is a node that has no connections with other nodes.
- Connected component is a group of nodes, where a path exists between each node pairs.
- Degree k_i is a number of neighbors of a node i.
- Density is a fraction of node pairs which are tied together.
- Modularity is a coefficient that indicates a tendency for nodes to be connected with nodes of their own community rather than nodes from other communities. In this study, communities were automatically detected by modularity maximization algorithm. This means that nodes were partitioned into communities in such a way that a modularity of this partition was the highest as possible (the maximum possible value is 1). Thus, the modularity is a measure of overall tendency of nodes to group into dense communities poorly connected with other communities. The formula for modularity is:

  $$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(c_i c_j)$$

  where A is a network adjacency matrix and c_i is an index of i-th node community.
- Transitivity coefficient is a clustering measure and is a fraction of connected triples that are also triangles:

  $$C = \frac{3 \times (number\ of\ triangles)}{(number\ of\ connected\ triples)}$$

  where C is transitivity coefficient.

- Average clustering coefficient is also a clustering measure. It shows density of an average node's neighborhood. The formula for this coefficient is:

$$C_{avg} = \frac{1}{n}\sum\nolimits_{i=1}^{n} C_i$$

where

$$C_i = \frac{2n_i}{k_i(k_i - 1)}$$

C_{avg} is average clustering coefficient, n is a number of nodes, k_i is a degree of i-th node, n_i is a number of i-th node neighbor pairs tied together, and C_i is defined as zero for nodes with degree 1 and is not defined for isolated nodes.

The network of school shooting communities' followers included 446 users, and the network of followers of suicide-related communities consisted of 11,898 users. Table 2 provides network characteristics of the investigated types of communities in details.

Table 2. Characteristics of networks of school shooting and suicide-related communities' followers.

Characteristics	Network of School Shooting Communities' Followers	Network of Suicide-Related Communities' Followers	Consolidated Network
Nodes	446	11,898	12,167
Number of links	590	2745	3183
Average degree	2.65	0.46	0.52
Modularity	0.33	0.94	0.93
Average clustering coefficient	0.48	0.18	0.19
Largest connected component size	30%	8%	9%
Number of connected components	9	843	9626
Fraction of isolated nodes	65%	73%	72%
Transitivity	0.25	0.12	0.18

Note: 4223 (25.8%) accounts were private and did not provide an access to their profile information or friend list and were excluded from the study dataset and the analysis.

Social networks are usually sparse networks, so as a network size increases, its density tends to zero, while the average degree of vertices tends to converge to a finite number. Considering this, the degree instead of density was used to compare how tightly vertices in networks were connected to each other. The degree distribution laws of both graphs had fat tails, and before we drown a conclusion on the average degree, we needed to make sure that it was finite. For that, the power law distribution in both networks were estimated with assumption that the power law appeared when the node degree xmin = 10. The 95% confidence intervals for the degree distribution exponent in the network of followers of school shooting communities and the network of followers of suicide-related communities were 2.612 to 2.768 and 2.668 to 2.670, respectively. As these values were close and both exceed the value of 2, the mathematical expectation of a vertex degree in both networks was finite.

The average degree in the network of school shooting communities' followers were more than five times higher than that in the network of suicide-related groups' followers. At the same time, modularity in the graph of the latter network was close to 1, and modularity in the graph of school shooting communities' followers was relatively small (0.33). From this, the school shooting fans' network was dense (high average degree) but with weakly distinguished communities (low modularity). In other words, an average school shooting communities' follower was included in a strongly connected group of peers. The network of suicide-related virtual groups' followers showed an opposite structure, i.e., its high modularity (0.94) reflected high fragmentation (presence of several weakly connected communities), while low average degree showed weak general connection. An average follower of suicide-related communities was in contact with limited number of peers and connections between them were not distributed throughout the network. In fact, the average degree of vertices in the followers' network of suicide-related virtual communities was too small, and the network breaks up into a large number of isolated components (i.e., 843 connected components of size 2 or more versus 9 similar connected components in the network of school shooting communities' followers). In addition, the size of the largest connected component in the network of suicide-related communities' followers reached only 8% of users versus 30% in the network of school shooting virtual groups' followers. Graphs of both communities (Figures 1 and 2) distinctly illustrate these data.

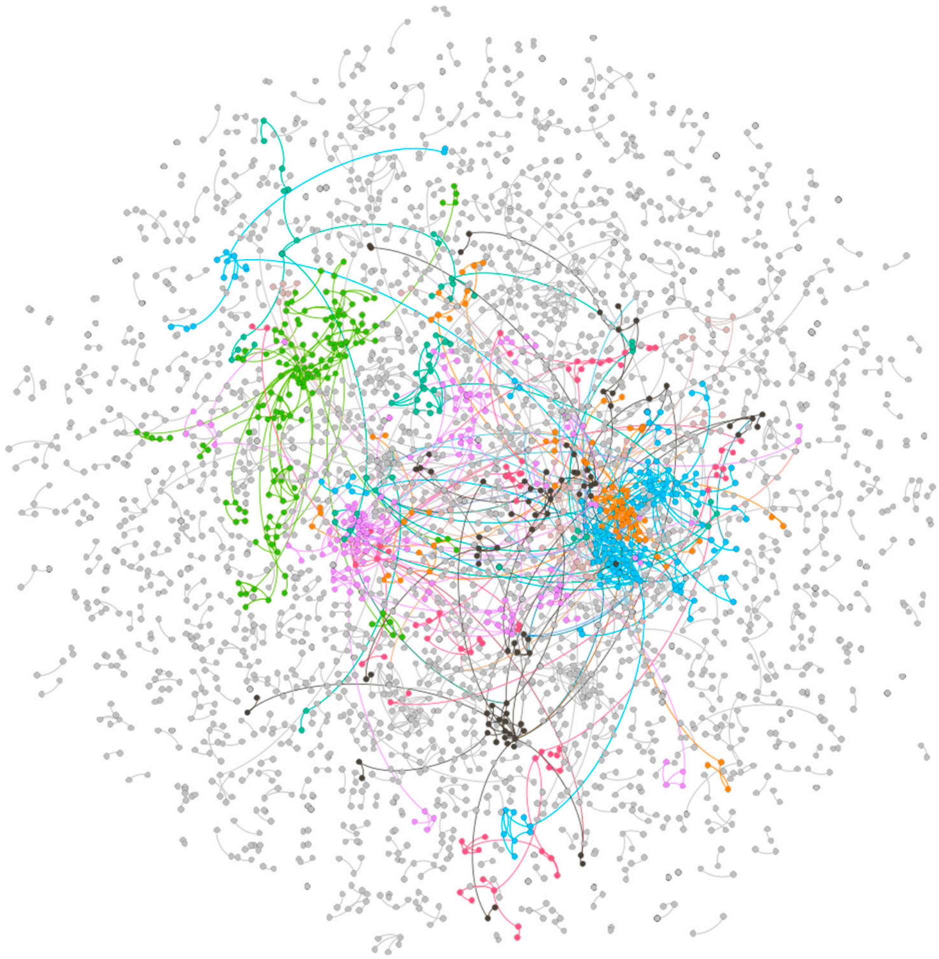

Figure 1. Followers' network of suicide-related virtual communities. In colors are different node communities detected by modularity maximization algorithm. For better visualization, isolated nodes were removed from the graph.

Obviously, the graph of suicide-related communities' followers shows several dense communities (Figure 1). However, the majority of investigated users are fragmented and divided into numerous relatively small communities, so the question on whether a giant connected component exists in this network of suicide-related communities can be raised. On the contrary, the graph of the network of school shooting communities' followers is small but quite monolithic (Figure 2).

Consolidated network comprises 12,167 nodes, 3183 links, and is rather scattered, with few links. Only 19 users (nodes) were included in both networks; therefore, these two segments were substantially unrelated to each other. The graph of consolidated network (Figure 3) illustrates sizes of the two investigated network segments and connections between them.

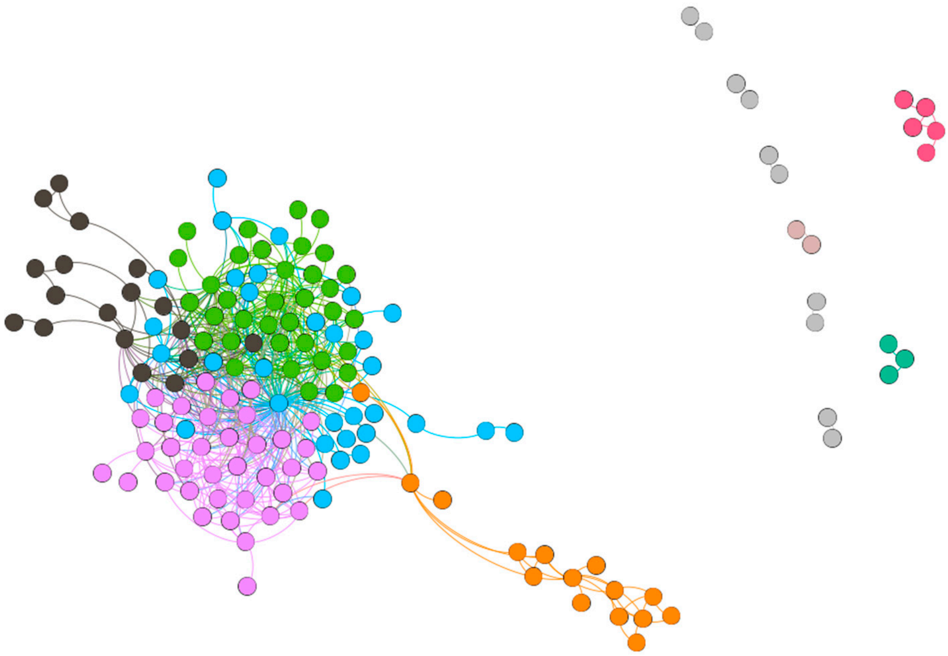

Figure 2. Followers' network of school shooting virtual communities. In colors are different node communities detected by modularity maximization algorithm. For better visualization, isolated nodes were removed from the graph.

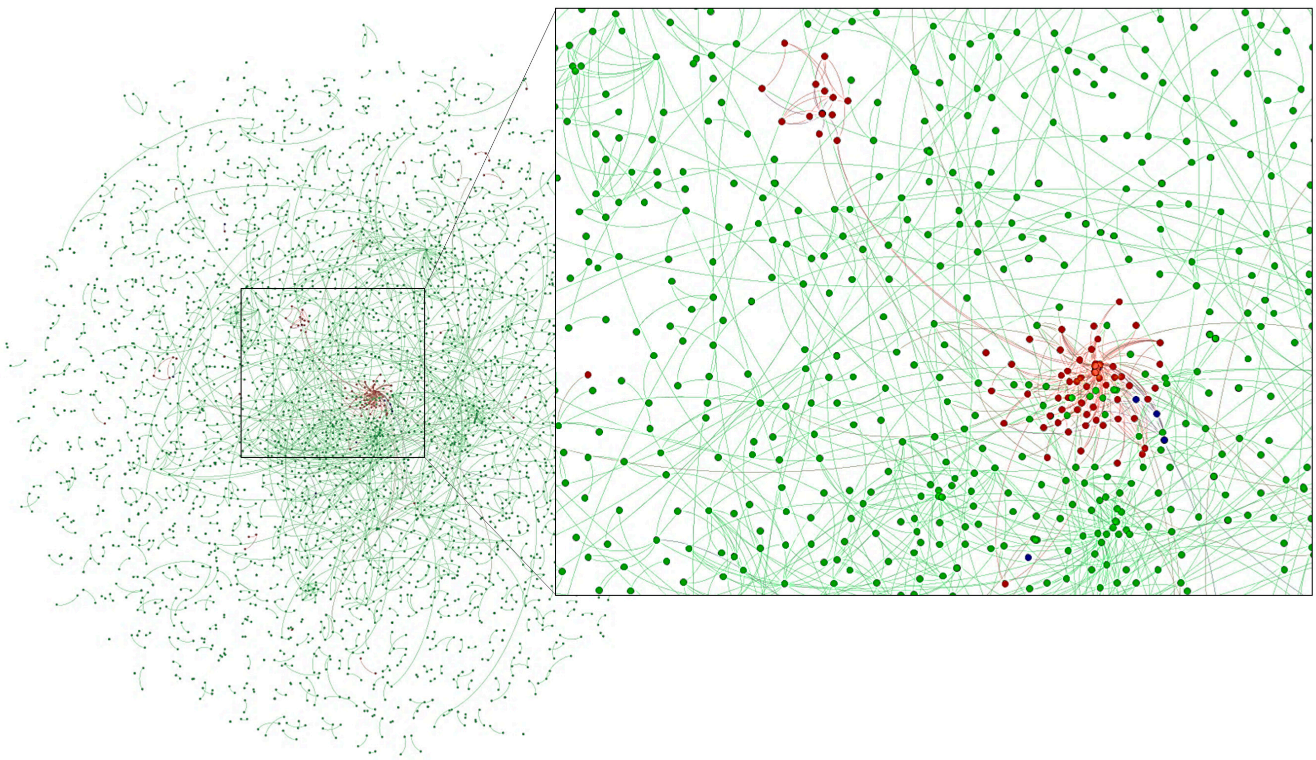

Figure 3. Consolidated network graph. Suicide-related communities' followers are colored with green, school shooting communities' followers are colored with red, and followers who subscribed to communities of both types are colored with blue. For better visualization, isolated nodes were removed from the graph.

There are two indicators of how nodes (or users) are included into their network; both are types of clustering measures: transitivity coefficient and average clustering coefficient (or average local clustering coefficient). Transitivity coefficient shows the likelihood that two friends of one social network's user are also each other's friends in this social network. For the networks we investigated, transitivity coefficients were 0.25 in the network of school shooting communities' followers; 0.12 in the network of suicide-related communities' followers; and 0.18 in the consolidated network. This means that the likelihood that two friends of one social network's user were also each other's friends was twice as high for school shooting virtual groups' followers. Members of the school shooting communities we investigated were more "included" into friendship network with their peers.

For scale-free networks (i.e., networks that have infinite second moment of a degree distribution), transitivity tends to zero as network size grows [39]. In our study, the network of school shooting communities' followers and the network of suicide-related communities' followers both were scale-free (power law exponents were less than 3). Thus, values of transitivity coefficient were highly affected by a neighborhood of higher-degree nodes in these networks. The distinctive feature we observed in the network of suicide-related communities' followers were higher degree nodes, or kind of hubs, which united a large number of unconnected users. In the school shooting followers' network, users were more included into peer network with friend links, and such hubs were less common.

Another measurement of clustering is an average clustering coefficient. Average clustering coefficient shows density of an average node's neighborhood and an average fraction of pairs of a user's friends who are also friends of each other. For scale-free networks, average clustering coefficient is more affected by lower-degree nodes. For the networks we investigated, the average clustering coefficient were 0.48 in the network of school shooting communities' followers; 0.18 in the network of suicide-related communities' followers; and 0.19 in the consolidated network. This indicates that an average follower of a suicide-related community was included into a sufficiently sparser group of peers then an average follower of a school shooting community.

4. Discussion

We employed basic demographics analysis and social network analysis to reveal common features, as well as distinct facets of the communities' structure and their followers' network. Results showed that followers of school shooting and suicide-related virtual communities were mainly youths aged less than 22 years with males prevailing among school shooting virtual community followers and females as the majority in some of the suicide-related virtual groups. The evidence obtained corresponds to the findings reported in our previous works [28,40].

The number of blocked communities related to school shooting was more extensive than that of suicide, which obviously coincided their radicalization potential because policy violations due to radicalization is considered among the most common reasons of blocking [41].

Our data also revealed that virtual school shooting communities could be recreated after blocking, and their followers could actively migrate from one virtual group to another if a community got blocked. These findings were confirmed by the results we obtained with social network analysis showed that followers of virtual school shooting groups were closely interconnected in their peer network with higher transitivity coefficient and the largest connected component covered one-third of a whole network. The transitivity coefficient was half as much in the network of suicide-related communities' followers, and the largest connected component in their network covered only 8% of their peers. Interestingly, this evidence did not confirm the findings reported earlier by Colombo and colleagues [38] on the high interconnection between users who authored suicide-related content on Twitter when they were compared with other Twitter users. In our study, we observed a network with low communicative integrity; however, we assume that a fullfledged and closely interconnected virtual segment of suicide-related groups' followers may exist.

In addition, despite the fact that followers of suicide-related and school shooting communities in our study were rather autonomous in their inter-segment communication (only 19 users were included in both networks), members of virtual school shooting groups showed interest in a suicide-related content either and subscribed to it. Followers of suicide-related virtual groups did not do that. As a possible explanation, school shooting refers to a delinquent behavior, which is manifested in actions that harm society. Such a behavior is not typically common for people with suicidal ideations, as they have self-harming intentions or even conduct self-harming acts [42–44]. Although it is a simplification of the issue discussed, it may explain why followers of suicide-related communities were less interested in school shooting information on social media and did not subscribe to it.

We intend for our findings to attract a broad audience of scholars, society authorities, and policy makers. As online networks and online subcultures can play a significant role in opinion formation [45–47], individual radicalization processes [48–50], self-harming behavior [51,52], and violence [53,54], we consider our results to be of high relevance for better understanding network aspects of virtual information existence, harmful information spreading among youth, and its potential impact on society.

5. Conclusions

The study findings indicated that youth aged less than 22 years were the main audience of virtual communities related to suicide and school shooting. The list of blocked communities related to school shooting was more extensive than that of suicide, which indicated a high radicalization degree of school shooting virtual groups. In addition, followers of school shooting fan communities expressed an interest in a virtual content related to suicide, whereas subscribers of suicide-related groups were not interested in a content of school shooting online subculture.

Social network analysis showed that the network of suicide-related communities' followers were large but fragmented and divided into numerous communities. On the contrary, the school shooting fans' network was small but dense and monolithic. Based on the average clustering coefficient, we found that an average follower of suicide-related community was included into sufficiently sparser group of peers then an average follower of school shooting fan community (0.18 versus 0.48 coefficient values). The size of the largest connected component in the network of suicide-related communities' followers reached only 8% of users versus 30% in the network of school shooting virtual groups' followers. Furthermore, members of school shooting fan communities were more "included" into friendship network with their peers than followers of suicide-related groups with network transitivity coefficient of 0.25 versus 0.12 in suicide-related virtual groups. In the latter network, there were higher degree nodes, which served as hubs and united a large number of unconnected users.

We conclude that our findings contribute to a better understanding of the demographics of users who consume harmful information on social media, their online behavior, and network characteristics.

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