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Understanding interactions in virtual HIV communities: A social network analysis approach

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Abstract

This study investigated the driving mechanism of building interaction ties among the people living with HIV/AIDS (PLWHA) in one of the largest virtual HIV communities in China using social network analysis. Specifically, we explained the probability of forming interaction ties with homophily and popularity characteristics. The exponential random graph modeling (ERGM) results showed that members in this community tend to form homophilous ties in terms of shared location and interests. Moreover, we found a tendency away from popularity effect. This suggests that in this community, resources and information were not disproportionally received by a few of members, which could be beneficial to the overall community.

Keywords: Weibo HIV community, social network analysis, homophily, popularity effect, PLWHA interactions

Understanding Interactions in Virtual HIV Communities: A Social Network Analysis Approach

The unprecedented popularity of social networking sites (SNSs) provides people living with HIV/AIDS (PLWHA) a novel platform to exchange social support (e.g., Shi & Chen, 2014), which may help them buffer HIV-related psychological distress (Simoni, Frick, & Huang, 2006). Meanwhile, examining the digital footprints the PLWHA left offers scholars a valid and unobtrusive means to understand their online interactions. Specifically, this study aims to explore the driving mechanism of building interaction ties in a virtual HIV community through social network analysis, therefore bringing theoretical as well as practical implications for future online HIV interventions. To achieve this objective, the current study counts on two fundamental principles of constructing social ties in sociology: homophily and popularity effect.

Homophily is a “striking and robust” principle in constructing social network ties (Kossinets & Watts, 2009), which denotes that a social connection is more likely to form between similar rather than dissimilar people (Burt, 1991; Marsden, 1988; McPherson & Smith-Lovin, 1987). Homophily is a multidimensional concept with a wide range of dimensions of similarity (Block & Grund, 2014; McPherson, Smith-Lovin, & Cook, 2001). In the current study, we focused on two types of similarities: shared location and shared interests.

Shared geographic location is the basic source of homophily (McPherson et al., 2001). For instance, on Twitter, members of the United States Congress tend to communicate with other members of the Congress from the same state (Peng, Liu, Wu, & Liu, 2014). In addition, geographic location is closely associated with the ethnicity, religion (Lieberson, 1980), and the local culture in which individuals are embedded. For HIV/AIDS, local culture shapes the social inequality and political economics relevant to HIV transmission and

prevention (Parker, 2001), and influences people's health perceptions towards HIV (Airhihenbuwa & Obregon, 2000). Thus, we proposed Hypothesis 1 (H1) as follows:

H1: Members from the same geographic location are more likely to interact with one another in virtual HIV communities.

Additionally, some research has showed that social networks are highly homophilous in terms of values (Richardson, 1940). Scholars have documented "hobby or interest homophily" online that individuals tend to befriend or interact with those who share similar interests (Yang et al., 2011). For instance, SNS users tend to create social ties with individuals who share similar tastes in music and movies (Baym & Ledbetter, 2009; Lewis, Gonzalez, & Kaufman, 2012). Thus, we proposed Hypothesis 2 (H2) as follows:

H2: Members with shared interests are more likely to interact with one another in virtual HIV communities.

On the other hand, the distribution of connections in social networks is uneven and follows a power-law distribution (Barabási, 2009). The most prominent explanation for this phenomenon is popularity effect: the tendency of network participants to connect with popular ones (Johnson, Faraj, & Kudaravalli, 2014). Nevertheless, research on popularity effect in virtual communities has yielded mixed results (e.g., Faraj & Johnson, 2011; Welles & Contractor, 2015; Utz & Jankowski, 2015). Thus, we asked research question 1 (RQ1) as follows:

RQ1: Is there a tendency for some members in HIV virtual communities to disproportionally received interaction ties from others?

Method

The HIV/AIDS Weibo Group is one of the largest public communities on Weibo (China's equivalent to Twitter) dedicated to HIV. It was created in January, 2011 and with 1,636 members. The current research included the data from 836 active members who posted

at least one message in the community. The data were extracted using Python Web Crawl (Russell, 2013) on February 27, 2014. The data includes: (i) the post-reply relationships among the 836 members; (ii) the participations in other Weibo groups ($n = 2,896$) of the 836 members; and (iii) the members' personal profiles, including one's location, gender, registration date, the number of posts, and the information of his or her followers and followings.

The interaction network was constructed in such a way that if group member i replied to the message posted by group member j , then i was connected to j . The direction of the tie was from i to j . We also constructed two homophily measures: 1) shared location. If group members i and j reported the same province in their Weibo profiles, then i and j were considered to have a shared geographic location. 2) shared interests. It was constructed through the members' shared memberships of other Weibo groups. If group members i and j joined the same type of Weibo group, then they were considered to have a shared interest¹. We employed geometrically weighted indegree distribution ($gwidegree$)² to measure the popularity effect.

We employed the exponential random graph model (ERGM; Robins, Pattison, Kalish, & Lusher, 2007) to address our hypotheses and research question. ERGM is one well-developed method for studying networks, which can estimate the effects of covariates on the formation of network ties while simultaneously estimating the forms of dependence that exist in relational data³ (Cranmer & Desmarais, 2011). We constructed the network and conducted the descriptive analysis as well as the ERGM using Statnet package in R (Handcock, Hunter, Butts, Goodreau, & Morris, 2008).

Results

The interaction network was sparse with 3,127 interaction ties and a density of .004. The reciprocity for the network was .301. The network was small-world with a large

clustering coefficient and a short network diameter (Watts & Strogatz, 1998). The average clustering coefficients of the network was 0.111, which was significantly greater than the average clustering coefficients of corresponding random networks. The diameters of the largest components in the network were 7, which was close to the six-degree separation rule (Milgram, 1967). The definitions of the above-mentioned network metrics are presented in Table 1.

The ERGM results showed that the homophily mechanism significantly and positively affected the tie generation in the network. As shown in Table 2, the homophily in location was positively associated with tie formation in the network. It means that, when everything else being equal, two members from the same location were more likely to interact with one another than two members from different locations. Thus, the data were consistent with H1, which predicted a positive effect of geographical homophily on creating interaction ties. H2 proposed a homophily effect of shared interests on building interactions. The results revealed that, when everything else being equal, two individuals within shared interests were significantly more likely to build interaction ties than two members without shared interests, which was consistent with H2. With regard to the RQ1 on popularity effect, we found that *gwidegree* was negatively associated with receiving an interaction tie from other members. It revealed a clear tendency that replies were homogeneously distributed over the interaction network, so the network was not centralized on indegree.

Discussion

The current study investigates the effects of homophily and popularity characteristics on the formation of interaction ties among the PLWHA in a virtual community on Weibo. Our findings show that members in this community tend to form homophilous ties in terms of location and interests. Furthermore, there is a tendency away from popularity effect in the tie

formation as well, which suggests an equal distribution of resources and information among the members.

In details, the homophilous characteristics, including shared location and interests, are positively associated with the tie formation in the HIV community. Indeed, interacting with similar others may enhance members' satisfaction with the community (Preece & Ghazati, 2001), and lead to an empathetic understanding and mutual support among group members (Wellman & Gulia, 1998). Thus, health professionals could create homophilous communities on SNSs including the PLWHA from the same location or enjoying similar leisure time activities. Such virtual communities may facilitate peer interactions and mutual support among the PLWHA. Nevertheless, homophilous networks have disadvantages as well, such as impeding new ideas and information (Valente, 2010). Furthermore, misinformation or rumors about HIV/AIDS could spread quickly because of the homophilous ties among peers. Thus, during an online HIV intervention, reducing the spread of rumors may also be critical in a homophilous virtual community. Yet this speculation needs further examinations.

Furthermore, our findings also reveal that the replies are not disproportionately directed to a few of members in this community, which shows a tendency away from popularity effect. One possible explanation could be that topic-oriented virtual communities (e.g., Faraj & Johnson, 2011) may differ from physical and technological networks in which popularity effect is generally applicable (e.g., Barabási, 2009). On the other hand, such phenomenon is beneficial to the overall HIV community. Since interactions in virtual HIV communities often carry social support (Chen & Shi, 2015), our findings indicate that these resources are not disproportionately received by a few of members in the Weibo group. Thus, all members in this community have chances to receive replies from others, which may help them to obtain useful resources.

Last, we have to acknowledge two limitations in the current research. First, we use cross-sectional data for investigating popularity effect, but future studies could examine such effect using longitudinal data. Second, we investigate only one community. Future research could replicate our research to increase the generalizability of the current findings on PLWHA's interactions in virtual HIV communities.

Footnotes

¹ Given that the 836 members in *The HIV/AIDS Weibo Group* have joined 2,896 other Weibo groups, we categorized these groups according to their themes. First, we randomly selected 300 groups (10.36%) to formulate an exhaustive coding scheme through the open coding method. Weibo groups were inventoried into 14 categories, including (a) HIV/AIDS, (b) homosexuality, (c) health, (d) non-governmental organizations, (e) professional groups, (f) hobbies, (g) fans, (h) parenting, (i) alumni, (j) politics, (k) religions, (l) social, (m) traditional media, and (n) miscellaneous (The definitions and examples of each category are provided upon request). After creating the coding scheme, we randomly selected a second set of 300 groups (10.36%) and independently coded them to build the inter-coder reliability (Krippendorff's $\alpha = 0.90$) (Krippendorff, 2011). Discrepancies were resolved through discussions. Finally, all 2,896 Weibo groups were split into four quarters and separately coded by the four authors.

² The gwidegree stands for a geometric statistic that inversely weighs the value of indegree as a node's count on statistic increases (Hunter, 2007). This term allows researchers to model the popularity effect in the formation of network ties (Hunter, 2007; Snijders, Pattison, Robins, & Handcock, 2006). A significantly positive coefficient for gwidegree implies that nodes with low indegree are more likely to form a link with those with high indegree in the network (i.e., the presence of popularity effect). Alternatively, a significantly negative coefficient indicates a preference towards the homogeneity of nodes' indegree. A non-significant coefficient suggests all indegree distributions are equally preferred (Lusher, Koskinen, & Robins, 2012).

³ The interpretation of an ERGM is a similar to the interpretation of a logistic regression. The dependent variable of an ERGM is a tie in a network, and the characteristics

of network members and network structures are included as independent variables to explain or predict the probability of a tie formation (Robins et al., 2007).

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Table 1

The Definitions of Social Network Metrics Used in the Current Study

Social Network Metric	Definition
Indegree	The number of ties that a node receives in a network.
Gwidegree	Gwidegree stands for a geometric statistic that inversely weighs the value of indegree as a node's count on statistic increases.
Density	The sum of the existing ties divided by the number of possible ties in the network.
Network reciprocity	The likelihood of nodes to be mutually linked in the directed network.
Clustering coefficient	A measure of the degree to which nodes tend to cluster together in the network
Diameter	The maximum distance between any pair of nodes in the network

Note. The definition of gwidegree was adapted from Hunter (2007), and the others were adapted from Scott (2013).

Table 2

The Exponential Random Graph Modeling (ERGM) Results of the Interaction Network in The HIV/AIDS Weibo Group

	Model 1		Model 2		Model 3	
	Coefficient		Coefficient		Coefficient	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Edges	-5.436***	0.018	-6.024***	0.096	-5.206***	0.075
Control variables						
Gender (Female = 0)			0.251***	0.050	0.085**	0.037
Experience			-0.000	0.000	-0.000	0.000
Activeness			-0.019***	0.009	-0.029***	0.008
The following network			1.802***	0.047	1.383***	0.045
Independent variables						
Homophily: shared location					0.198***	0.067
Homophily: shared interests					0.086***	0.015
Popularity effect: gwidegree					-3.573***	0.083
Log-likelihood	-19,494.96		-18,941.9		-18,088.4	
Akaike information criterion	38,992		37,894		36,193	
Bayesian information criterion	39,003		37,951		36,284	

Note. s.e. = Standard error. Experience is the number of days from the user's registration date till February 27, 2014. Activeness is the average number of messages a user posted daily on Weibo during his/her registration. The following network is constructed using their following relationship on Weibo. It is constructed in such a way that if group member i follows group member j , then i is connected to j , and the direction is from i to j .

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.