Social Capital and Participant Retention in Online Mental Health Community: Quantifying the Relative Effect of Bridging and Bonding Social Capital

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Abstract

We examine the effect of social capital on participant retention in online mental health community, and disentangle the effect of bridging and bonding social capital on participant retention in this paper. Specifically, we derive participant profile data and activity data for 15 years from a Chinese online mental health community and construct social networks based on reply relationship for every half year. Following prior studies, bridging social capital and bonding social capital are measured by structural holes and network closure respectively. We conduct survival analysis to examine whether social capital has effect on participant retention, and use panel Logit model to capture the efficacy of different types of social capital. Results show that social capital significantly improves participant retention rate; bridging social capital has positive effect on participant retention, whereas bonding social capital has negative effect on participant retention.

Keywords: Online mental health community, bonding social capital, bridging social capital, participant retention, survival analysis

1. Introduction

Social media has changed the way we interact and communicate with each other. It offers people who may be suffering from mental health crisis an opportunity to seek help from others, and enables them to listen to and understand the health experiences of others. Research into this phenomenon suggests that this kind of behavior may be hugely beneficial to those experiencing mental health issues (Yan and Tan 2014). On the one hand, social media provides a low-cost opportunity to spread mental-health information virally (Pan et al. 2017); on the other hand, it promotes connectedness, social support and social influence, which facilitate healthy behavior and personal recovery (Poirier and Cobb 2012). Although social media has the potential to positively affect people's mental health, its effectiveness highly depends on participants' usage (Eysenbach 2005). Thus, it is important to improve loyalty and retention in online mental health community.

Through the network of relationships and information exchange, participants derive the actual and potential resources, i.e., social capital. The association between social capital and health outcome, especially mental health, has established for the past decade (e.g. De Silva et al. 2007; Yamaoka 2008). Nonetheless, little is known about the potential effect of social capital on participant retention and mechanisms by which social capital exerts such effects in the online mental health community. This has motivated us to investigate the role of social capital in great depth by disentangling the effect of bridging and bonding social capital on participant retention. And this work is based on the following considerations:

First, though there are many prior studies on the effect of social capital, little has shed light on the potential impact of social capital on mental health and user retention in online health community. Researchers have studied the effect of social capital on mental health in various offline environment, such as neighborhood community (Ziersch et al. 2005), worksites (Liukkonen and Vertanen 2004) and found social capital is a relevant determinant for mental health outcomes. Regarding online mental health community, researchers have examined the effect of social support (Yan and Tan 2014) and social anxiety (Ruppel and Mckinley 2015), but few research has been looking at the impact of social capital.

Second, there is little research involved in the efficacy of different types of social capital on mental health and user retention. It is a challenge to distinguish positive social capital and negative social capital (Campbell 2000), which varies with different contexts. Thus, it is important to examine the effect of different types of social capital. However, there is no consensus about the relationship between bonding social capital and mental health. For example, Kawachi and Berkman (2001), Mitchell and La Gory (2002) found social engagement in close-knit community has damaging effect on mental health, whereas others found that bonding social capital plays an important role in promoting mental health (Kim et al 2006; Poortinga 2012). In this study, we disentangle the effect of bridging social capital and bonding social capital on participant retention in online mental health community.

Third, while most studies are secondary data analyses of survey data, this has led to a lack of depth of investigation of social capital. There are no united measuring indicators of social capital at present. For example, Liukkonen et al. (2004) examined the effect of social capital in the context of workplace, and social capital are measured by security of the employment contract and trust in co-work support. Nyqvist et al. (2008) used social participation, social contacts, trust, sense of security to measure social capital. In this paper, we take the view of network and measure social capital following Lin et al. (2001).

Our research questions are: whether social capital affects participant retention in online mental health community? How different types of social capital, i.e. bridging social capital versus bonding social capital, affect participant retention?

To study our research question, we collect a novel dataset from a Chinese online mental health community (http://www.sunofus.com/). Participants in this community could post content for sharing experience, gathering information and seeking help, and others could involve in topic discussion and respond to posts they are interested in. In this respect, social networks based on reply relationships offer us an opportunity for precisely measuring bridging social capital and bonding social capital, and examining the effect of different types of social capital on participant retention. We conduct survival analysis to examine whether social capital has effect on participant retention; and we use panel Logit model to capture the efficacy of different types of social capital. We find that, social capital significantly improves participant retention rate; bridging social capital has positive effect on participant retention, whereas bonding social capital has negative effect on participant retention.

This study has potential to contribute to social capital and mental health literature. First, it explores the effect of social capital on participant retention in online mental health community; second, it helps us to understand the effect of bridging and bonding social capital on participant retention. Online mental health community could initiate strategies that enhance bridging social capital to support sustained use of platform.

2. Literature Review

In this section, we briefly summarize streams of literature that inform our study: (i) social capital and mental health; (ii), user retention in online community.

2.1 Social Capital and Mental Health

Social capital could be roughly defined as “the goodwill that is engendered by the fabric of social relations and that can be mobilized to facilitate action” (Lin et al. 2001; Kdler and Kwon 2002).

There are different types of social capital. One key distinction can be made between bridging and bonding social capital (Putnam 2000). The difference between bonding and bridging social capital includes the relationships within/between social groups, sociodemographic or socioeconomic characteristics and the strength of ties. Bonding social capital is within a community where people are alike, whereas bridging social capital is between communities and derived from people who are different.

The concepts of bridging and bonding social capital are related with structural holes and network closure in social network theory (Kdler and Kwon 2002). When others are indirectly connected through one specific individual but do not have direct ties, structural hole exists. As a result, this specific person has access to lots of information and resources, i.e., s/he is a broker and with high bridging social capital. Thus, following prior studies, we measure bridging social capital by network betweenness that is an index indicating the extent to which an individual brokers indirect connections with others (Ganley and Lampe 2009; Pan et al. 2016).

Bonding social capital comes from network structure of closure. The network closure is the extent to which individuals are connected to each other in a network. It affects access to information because individuals are closely tied and boosts emotional support for one other (Williams 2006). We measure bonding social capital by network closeness.

Researchers have found social capital is positively associated with mental health (e.g. Ziersch et al. 2005). These studies are mainly based on offline environment, such as specific geographical area, nation-wide and population-based. For example, Rose (2000), McCulloch (2001), Lindström (2004), Pollack and von dem Knesebeck (2004), Ziersch et al. (2005), and Phongsavan et al. (2006) studies the effect of social capital in nation-wide and found social capital is positively related to mental health. Veenstra et al. (2005) found social involvement has a positive effect with mental health. Regarding mental health in online community, Yan and Tan (2014) found social support is helpful for mental health based on data from an online depression forum.

As to the effect of different types of social capital, a few studies have disentangled between bridging and bonding social capital. However, there is no consensus about the effect of bonding social capital. Kawachi and Berkman (2001), Mitchell and La Gory (2002) found bonding social capital has damaging effect on mental health, whereas others found that bonding social capital plays an important role in promoting mental health (Kim et al. 2006; Poortinga 2012). In this paper, we examine the effect of different types of social capital on participant retention in online mental health community.

2.2 User Retention in online community

The literature on online community found social influence, social interaction, and member attachment are crucial to retention (Richardson et al. 2010; Boston et al. 2011; Ren et al. 2012).

Social influence stems from the transmission of information among people in social network. The transmission of information can occur through a variety of social interactions. In this process, one could help others or receive help, i.e. social support. Research have found social support, social interactions and social influence all have positive effect on user retention in different types of online communities, such as online learning community (Boston et al. 2011), online health community (Richardson et al. 2010) and social commerce platform (Nitzan and Libai 2011).

Member attachment is affective connection to and caring for an online community in which they become involved. Members with high attachment are more willing to post and reply content in online community, thus with high retention rate (Preece 2000; Ren et al.2012). To strength members' attachment, increasing interpersonal bonds, such as communicating with like-minded people, is an effective strategy (Ren et al. 2012). This also could promote bonding social capital.

In this study, we will study the effect of social capital on user retention in online health community.

3. Model Specifications and Data

This study analyzes the participant retention in online mental health community in two aspects. First, we study the distribution characteristics of participant retention periods by Kaplan-Meier method. Second, we use discrete choice model to further examine the effect of different types of social capital on participant retention.

3.1 Model Specifications

3.1.1 Survival Analysis

In this study, we use Kaplan-Meier procedure to measure the retention periods of participant. It is a useful method to deal-with right-censored problem. The estimator of survival rate is as follows:

$$\hat{S}(t) = \prod_{i:t_i \le t} (1 - \frac{d_i}{n_i}), \tag{1}$$

where $\hat{S}(t)$ is the estimator indicating retention time is greater than *t*, t_i is a time when at least one participant churn, d_i is the number of participants who churn at time t_i, and n_i is the number of participants who retain (have not yet churned or been censored) at time t_i.

We use survival analysis to analyze the overall distribution of participant retention time, and determine if there are systematic differences between bridging social capital and bonding social capital.

3.1.2 The Effect of Social Capital on Participant Retention

After survival analysis, we conduct discrete model to examine the effect of social capital on participant retention. The model specifications are as below:

$$h_{ij} = P(T_i = j \mid T_i \ge j), \tag{2}$$

where T_i is participant *i* retention time, h_{ij} is hazard rate in the *j*th period. h_{ij} means participant churn in the *j*th year after retaining *j* periods. And we use c_{ij} to denote whether participant *i* is right-censored. It equals 1 if we could observe his churn time and 0 if data is right-censored. The log-likelihood function for full sample is as follows (Jenkins 1995):

$$\ln L = \sum_{i=1}^{n} c_{ij} \ln(\frac{h_{ij}}{1-h_{ij}}) + \sum_{i=1}^{n}\sum_{k=1}^{j} \ln(1-h_{ik}) \tag{3}$$

In order to translate model (3) into a discrete model, we define a binary outcome variable "$churn_{ij}$" to represent whether participant i churns in the jth period. If c_{ij} is 0, $churn_{i1}$= $churn_{i2}$=……$churn_{ij}$=0; if If c_{ij} is 1, $churn_{i1}$= $churn_{i2}$=……$churn_{ij-1}$=0 and $churn_{ij}$=1, that is,

$$c_{ij} = \sum_{k=1}^{j} churn_{ik} \quad . \tag{4}$$

Plug Formula (4) into (3), we could get

$$\ln L = \sum_{i=1}^{n}\sum_{k=1}^{j} [churn_{ik} \ln h_{ik} + (1-churn_{ik}) \ln(1-h_{ik})], \tag{5}$$

h_{ij} is the probability that $churn_{ij}$ equals to 1. According to discrete model, probability h_{ij} could be modeled as:

$$h_{ik} = F(X_{ik}\beta + \nu_i + \eta_t + \varepsilon_{it}), \tag{6}$$

where X represents independent variables, ν_i is individual effect, η_t is time effect and ε_{it} is error term. Key independent variables include bonding social capital, bridging social capital, in-degree (take log) and out-degree (take log). We conduct logit transformation for formula (6) and estimate it using panel data logit model. In order to avoid reverse causality issue, we model participant churn in period t+1 using independent variables in period t.

3.2 Data

Data in this study is derived from Sunofus (www.sunofus.com/), which is a famous online mental health community in China. We extracted all of the information that participants provided (including user name, user registration time, post and reply time, post and reply content) in December 2017. The full sample is composed of 35193 users who had created 81283 threads and posted 835096 replies from January 2003 to December 2017. In this sample, only 10443 participants have made posts or replies. We extract these participants and their activities from our full sample in order to focus on our analysis of participant interaction and retention during the research period.

Based on participants' reply relationship, we could construct a social network to measure participants' social capital. As shown in the Figure 1, participant A, participant B and participant C all have made posts or replies at least once. A link from participant A to participant B means that A replies to B's post. If participant A replies to B twice in a given period, the strength of this link is 2. In addition, participant C replies to B three time and replies to A four times. Thus, the in-degree of participant A is 4, and out-degree of participant A is 2.

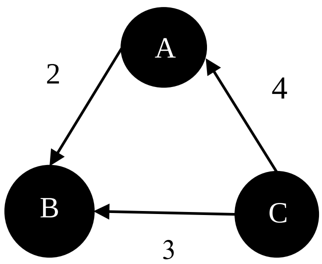


Figure 1. An example of reply network

Following the above network construction approach, we construct social network for every six months. Here, following prior studies (e.g., Mutanen 2006), we take six months as a churn period. Therefore, we have 30 periods and corresponding social networks, and transform these social networks into adjacency matrices. The matrices are weighed networks with numbers in the cells representing the reply number between two users. We analyse these matrices using R package *igraph*, calculating network statistics including in-degree, out-degree, network betweenness (bridging social capital), and network closeness (bonding social capital). It is worth to note that in-closeness and out-closeness are both measured.

Furthermore, we need data for dependent variable, i.e., participant retention. Sunofus keeps user activity log, including last visit time, last action time, and last post time. Here, we take user last visit time as his churn time. The outcome variable of discrete choice model "*churn*" in this corresponding time period takes 1, and takes 0 in other time periods.

Finally, the last six months of 2017 serves as the right-censoring time period for the study. At the end of 2017, the time we collected the data, many of the participants were still in activity, so we have no information on their actual churn. We thus treat these cases as right-censored. The Kaplan-Meier method we use could solve this problem.

Detailed summary statistics are presented in Table 1. We take log for the variables In-degree, out-degree, betweenness, in-closeness, and out-closeness.

Table 1. Summary Statistics for Covariates

Variables	Mean	Std.Dev.	Min	Max
Churn	0.235	0.424	0	1
In-degree	1.548	1.394	0	7.493
out-degree	1.417	1.361	0	7.542
betweenness	2.563	3.406	0	13.039
in-closeness	-13.855	0.945	-15.302	-6.890
out-closeness	-13.642	1.040	-15.302	-7.256

4. Empirical Results

4.1 Distribution of Participant Retention Periods

We use survival analysis to analyse the overall distribution of participant retention time, and then determine if there are systematic differences across bridging social capital and bonding social capital. Survival rate is the most important indicator to describe participant retention. Here, we use Stata 14.0 to plot Kaplan-Meier survival curves.

(1) Survival curve for full sample. Figure 2 show the Kaplan-Meier survival curve for full sample. We could see that (a) large declines appear in the first three periods. About 35% of Participants churn at the end of first period, and only 28% of participants retain for 3 years (6 periods); (b) the survival function shows a more moderate decline at later times than that of early times; (c) there is threshold effect, that is, if participants have retained for 20 periods, the probability of churning become significantly lower.

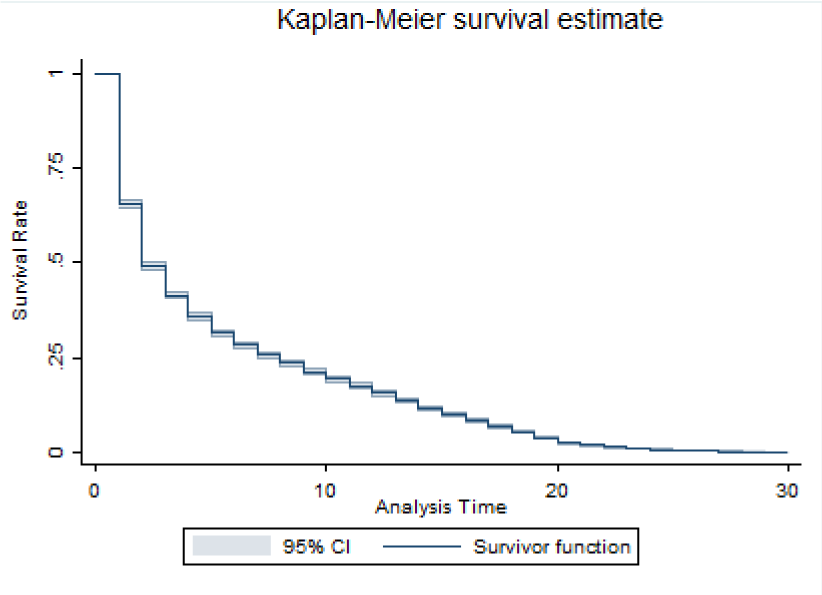


Figure 2. The survival curve for full sample

(2) Survival curves by bridging social capital. We plot survival curves by bridging social capital to examine the effect of bridging social capital on retention. We first generate the mean of network betweenness for each participant across periods. If the mean network betweenness for a participant is higher than median, we classify this participant as high bridging social capital one, otherwise low bridging social capital one. As shown in Figure 3, there is great difference between participants with high bridging social capital and participants with low bridging social capital. The survival rate for high bridging social capital participants is greater than that of low bridging social capital participants.

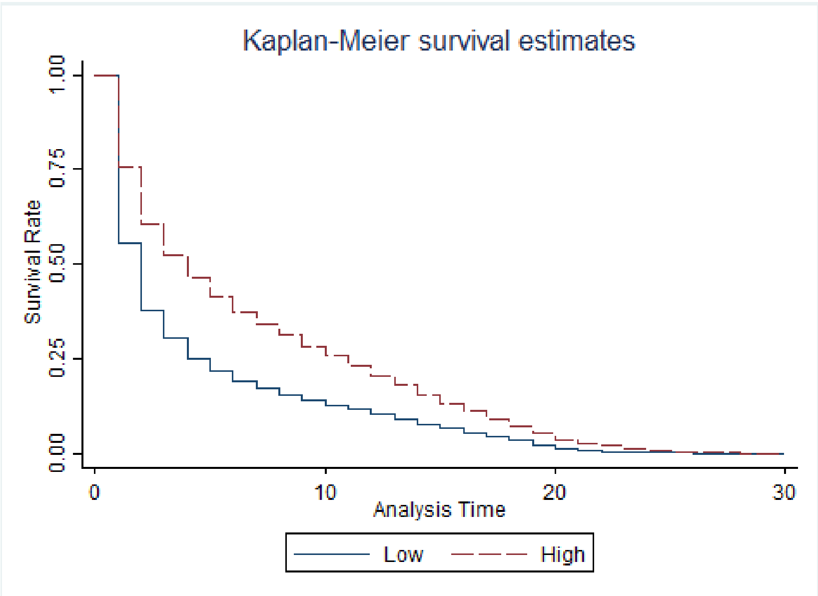
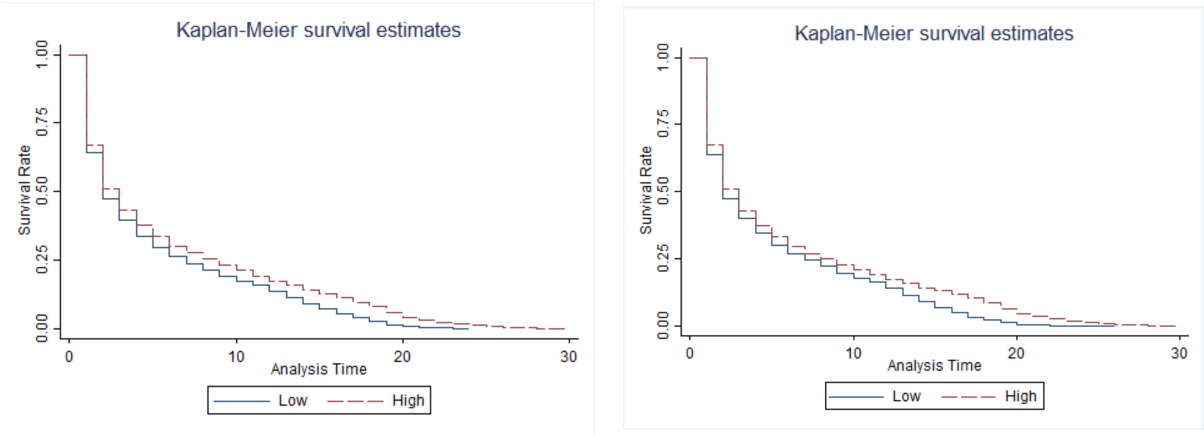


Figure 3. The survival curve by bridging social capital

(3) Survival curves by bonding social capital. Following the procedure of plotting survival curve by bridging social capital, we also plot survival curve by bonding social capital (Figure 4). The change trends between participants with high bonding social capital and participants with low bonding social capital are quite similar. However, survival rate for participants with high bonding social capital are still greater.



(a) in-closeness (b) out-closeness

Figure 4. The survival curve by bonding social capital

4.2 The Effect of Different Types of Social Capital On Participant Retention

We conduct conditional random effect logit estimation to examine the effect of different types of social capital on participant retention. Since the coefficients of the logit model do not have economic meaning, we also report the marginal effect and odds ratio estimated by the panel logit model (Table 2). However, since the marginal effect changes with the change of the interdependent variables for nonlinear model, the odds ratio is the ratio of participant churn probability to the participant survival (retention) probability. Thus, we use odds ratio to indicate the effect of social capital on participant churn (Column 3 of Table 2).

Table 2. Results for the effect of social capital on participant churn

Variables	Coefficient	Margins	Odds ratio
In-degree	-0.202*** (0.034)	-0.036*** (0.006)	0.817*** (0.028)
out-degree	-0.475*** (0.033)	-0.085*** (0.006)	0.622*** (0.021)
betweenness	-0.006*** 0.002	-0.001*** (0.0003)	0.993*** (0.015)
in-closeness	0.234** (0.094)	0.042** (0.017)	1.264** (0.119)
out-closeness	0.277*** (0.058)	0.050*** (0.010)	1.319*** (0.077)
Individual	Included	Included	Included
Time			

Note: ***p<0.01, **p<0.05, *p<0.1 The values in parentheses are standard deviations.

The odds ratio reflects the change of ratio with 1 unit change of independent variable. If coefficient of odds ratio is higher than 1, the independent variable has a negative effect on participant churn rate, that is, it is helpful to participant retention; if coefficient of odds ratio is lower than 1, the independent variable has a negative effect on participant retention. We could see that bridging social capital (*betweenness*) has positive effect on participant retention, and bonding social capital (*in-closeness* and *out-closeness*) has negative effect on participant retention. These results are consistent with Granovetter (1977) and Putnam (2000), which state bridging social capital could bring more positive outcomes.

5. Discussion and Conclusions

In this study, we examine the effect of social capital on participant retention in online mental health community, and disentangle the effect of bridging and bonding social capital on participant retention. We derive participant profile data and activity data for 15 years from a Chinese online mental health community and construct social networks based on reply relationship for every half year. Following prior studies, bridging social capital and bonding social capital are measured by structural holes and network closure respectively. We conduct survival analysis to examine whether social capital has effect on participant retention; and we use panel Logit model to capture the efficacy of different types of social capital. We find that, social capital significantly improves participant retention rate; bridging social capital has positive effect on participant retention, whereas bonding social capital has negative effect on participant retention.

This study has the following research limitations. First, prior studies mainly focus on the effect of social capital on mental health in offline environment and online health community. However, the effect depends on participant usage of online community. We examine the effect of social capital on user retention, and our findings support that this paper has the potential to help researchers develop a more comprehensive understanding of the mechanism of social capital on mental health. Second, we disentangle the effect of bridging social capital and bonding social capital, which could help researchers have deeper understanding of different types of social capital. Third, our results are more generalizable, considering our panel data of a large online mental community rather than a study based on specific geographic area.

As for managerial implications, first of all, social capital is effective for participant retention in online health communities given our results. Thus, it is meaningful to encourage participant to actively create content and reply others' post. For example, platforms could provide some incentives for users' reply behavior. Second, the efficacy of bridging social capital and bonding social capital are different. Platform could observe users' reply behavior, and encourage user to develop relationship with others who are not similar with her/him.

This study also has limitations. First, we only examine the effect of reply relationship on participants' churn behavior, which is only an aspect of participant behavior. Future study could expand the analysis to include other behavior, such as following relationship. Second, we did not analyze content posted by users. Text mining techniques can be used in the future to determine the strength of user relationships. We have collected data and will analyze in the next step.

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