The Effect of Structural Holes on Social Capital and Individual Performance Within Social Media Networks

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Abstract. The increasing use of social media has transformed the way that individuals interact with each other and has accelerated the exchange of information and knowledge. Social media has also created the phenomenon of social capital defined as the expected collective or economic benefit derived from the cooperative interaction between individuals and groups. Our research paper explores the effect on structural holes on social capital and participant performance. Structural holes have been defined as weak links to other social media groups outside the primary social network group. Research posits that weak links generate more alternate sources of new information and knowledge than strong links and thus, create more social capital and affect individual performance within a social network. Our results discuss the effect of frequency of user logins, posts counts and hierarchy (as a measure of structural hole) on experience and activeness as a measure of individual performance.

Keywords: Social media networks · Social capital · Structural holes · Hierarchy · Virtual community

1 Introduction

Social media (e.g., Facebook, Twitter, and LinkedIn, etc.) represents one of the most influential forces in our society and impacts all aspects of IT and information sharing [3]. Social media provides interaction among individuals in virtual communities and social networks which are created to share or exchange information, ideas and knowledge [1]. Social media has also been defined as a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 technologies which include social networks, blogs, wikis, video sharing, and web-based applications to create user-generated content [13].

The increasing use of social media has transformed the ways that individuals interact with each other [3]. Additionally, social media has accelerated the exchange and the transfer of knowledge and information to further create "social capital" [6]. Social capital has been defined as the expected collective or economic benefit derived from the preferential treatment and cooperation between individuals and groups [18]. Although different social sciences may emphasize different aspects of what constitutes social capital, these disciplines agree that social networks generate "value" and social

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contacts which may positively affect the productivity of individuals [18]. The development of social capital engenders competitive advantages similar to the benefits derived from financial and human capital. The social capital embedded within social networks may engender more information and knowledge sharing, career opportunities, and other intrinsic rewards.

A widely accepted social capital metaphor is that people who are successful are somehow better connected [8]. But how does one define a "better" connection? Burt [6–8] posits that the "structural" position of a participant within a social media network determines his/her access to social capital. Therefore, a better structural position within a social media network may lead to "better" connections. Our research paper explores the effect of structural holes on social capital and individual performance. We begin with a brief review of the literature and propose hypotheses to be tested. Next, we describe the empirical data used for our study using the Social Network Analysis (SNA) tool to analyze the social structure of our data set. We then test our hypothesis using structured equation modeling (SEM) techniques. Finally, we discuss our results, their implications for future research and conclusions from our findings.

2 Literature Review

Social capital exists where individuals exert a competitive advantage because of their relative location within a social structure [7]. The relationship between social capital and success was observed as early as the 19th century by Alexis de Tocqueville. The proliferation of various social media networks has created new social capital applications which generate new and interesting trends and developments. The link between social capital and success has been related to the structural "position" of a particular individual within a social media network [6]. Individuals whose social networks bridge across different and external sources of information appear to have a competitive advantage in detecting new and rewarding opportunities [7]. These individuals are better positioned to broker new information and translate it into a "vision" [7].

However, researchers differ with regard to what constitutes a "better" position within a social network. The "*Strong Link*" theory posits that opinions and behavior are more complete and homogeneous *within* groups than across different groups [7]. Additionally, social media groups with dense internal connections facilitate the rapid spread of key information [8]. However, while individuals within strong link social media groups may efficiently regenerate the same information, new or incremental knowledge is not being distributed. Additionally, members from "strong link" groups often require higher "maintenance" in the form of continued communication and periodic "touching base" with other group members. Subsequently, "strong link" social media may not be effective in disseminating new information or new knowledge [7].

Conversely, the "*Weak Link*" theory posits that while participants within the same social media group may efficiently disseminate existing information, connections that span across different social media networks are more effective in generating new sources of information. Alternative viewpoints are the mechanism by which social

capital is created [7]. Weak links or sparse connections between heterogeneous social media participants facilitate the diversity of information diffusion across different groups. Additionally, weak links do not require the same level of communication maintenance as strong links do. Weak links to social media groups outside a primary group are referred to as "*structural holes*" [6]. Prior empirical evidence supports the effectiveness of structural holes in disseminating new information and knowledge that creates social capital and enhances individual performance [7].

Researchers propose different measures of *structural holes*. Among them are *ego* and *constraint*. Ego is defined as the smallest unit of analysis (as an individual "focal point") in a social network node [12]. An individual (i.e., ego) possesses high bargaining power if other participants within a particular social network are restricted to trade or interact only with that particular individual. Conversely, such individuals will have low bargaining power if other individuals are not constrained to a particular individual network and can interact with other participants. *Constraint* measures the extent to which *ego* is restricted by its the relationships to participants [8, 9, 11].

Another measurement of structural holes is *hierarchy*. Hierarchy measures whether structural constraint is concentrated on certain users or if it is distributed evenly among other participants [8, 9, 11]. The value of hierarchy indicates dependency (of ego on the social network neighborhood) and inequality (of the distribution of constraints across the social network neighborhood). The higher the value of hierarchy, the more unequal the strength of the relationships distributed across a particular social network, creating a greater probability that new information and will more easily diffuse among heterogeneous participants.

Research suggests that individual performance within social media networks may be approximated by the *quantity* and the *quality* of interaction between users and the information shared on a website [15]. For our study, *experience* is defined as the frequency a user accessed and interacted with the MITBBS website. The more frequently a user accessed a website, the more experienced a user becomes with the website and related virtual community of that particular discussion forum. *Activeness* is an indicator of the quality and frequency of meaningful posts and replies to queries by a user within a particular discussion forum. The value of activeness for example, is increased if the user actively replies to other posts and queries and created discussion threads that were, for example, selected as "top ten threads" on a certain day.

3 Research Model and Hypotheses

Prior research supports the fact that information brokers whose social networks span across diverse sources of information can provide critical information and knowledge to organizations [7]. Individuals whose social network span across structural holes have easier access to diverse information and knowledge which may provide them with a competitive advantage in generating new ideas and innovations. Individuals with a "better" structural position such as *hierarchy* within a social media network may engender better performance in the form of experience value and activeness value.

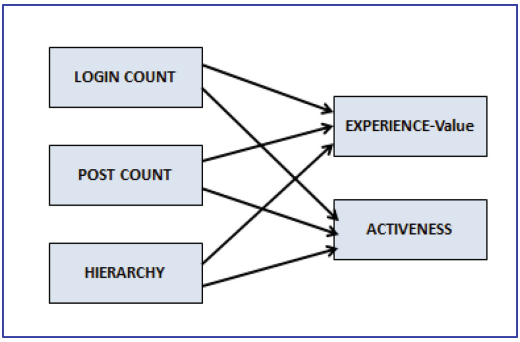

Fig. 1. Preliminary research model

Based upon the previous discussion and prior research findings relating to social capital, structural holes and individual performance within social network communities we propose the following research model (see Fig. 1) and related hypotheses.

H1. The higher the value of hierarchy, the higher the user experience value.
H2. The higher the value of hierarchy, the greater the extent of user activeness.

We propose that the frequency of online behavior on social network websites affects individual performance. For example, the more frequently a user logs on to a particular discussion forum, the more experienced that user becomes with that website and the related virtual community of that particular discussion forum. Additionally, the more frequently a user logs onto a particular discussion and maintains interaction with other forum users, the higher the activeness value of that user. Therefore, we propose the following hypotheses:

H3. The more frequently a user logs on to a website, the higher the experience value of the user.
H4. The more frequently a user logs on to a website, the greater the extent of activeness of the user.

We also propose that the frequency of user posts comments within a particular social network website affects individual performance. For example, the more frequently a user posts comments, replies or opinions to queries and threads on a particular discussion forum, the higher the experience value of that user with that particular social website. Additionally, the more frequently that a user maintains interaction with other users by posting comments, opinions and replies to other users, the higher the activeness value of that user Therefore, we propose the following hypotheses:

H5. The more frequently a user posts comments on to a website, the higher the experience value of the user.
H6. The more frequently a user posts comments on to a website, the greater the extent the activeness of the user.

4 Data Collection

We selected the social network website MITBBS (www.mitbbs.com), a Chinese bulletin board system to explore how structural position (i.e., structural holes) affects social capital and individual performance. The MITBBS website was built in 1997 by Chinese students from the Massachusetts Institute of Technology. MITBBS provides the most popular discussion forums for Chinese students studying abroad with a large variety of bulletin board topics such as entertainment, sports, literature, career advice and employment opportunities.

Data from the MITBB was selected for our study for the following reasons. First, MITBBS is an active discussion forum with intensive social interactions. Second, while the users of MITBBS are primarily Chinese students studying abroad, these students are located throughout the world and have varied backgrounds and interests. Our sample data sample therefore, was diversified and the social media networks they formed demonstrated various configurations. Third, the MITBBS website maintains records of all online discussions for several years and publishes usage data (e.g., actual posts, log times) by individual user account. These archival features provided researchers the opportunity to collect and mine data from the MITBBS website.

MITBBS possess hundreds of thousands of registered users which does not include guest users who may browse in and out without posting comments or replies to threads. MITBBS hosts over 300 discussion forums which are classified into 13 major categories. Table 1 displays the range of discussion forums hosted on the MITBBS website. Chinese students studying abroad and away from their families often must become self-sufficient within a completely new environment. Websites like MITBBS become a valuable virtual community where users can share and search for information, find friends and obtain news and entertainment. Within virtual communities such as MITBBS, social interaction occurs extensively online. Once a discussion "thread" is posted, an ID (i.e., registered user of the website) will receive responses from other IDs within that discussion forum. ID users become familiar with each other by posting and replying to discussion queries and threads.

As the purpose of our research was to explore how the structural position of users within social media networks would enhance social capital and individual performance, our study focused on analyzing interactions from those discussion forums that exchanged information and knowledge instead of forums that supported sports or pure entertainment. We selected "Academic Disciplines" from the major categories in Table 1 and then selected the "Business" discussion forum under this category. Within the Business discussion forum we analyzed IDs (users) that focused on school ranking, major areas of study, career development, professional licenses, job interviews and topics related to the study of business and business career opportunities.

5 Data Measurement

Two types of data were collected to empirically test our hypotheses. First, we collected data which recorded the behavior and the performance of individual users. This data was found via the user's personal page posted on the MITBBS website. Each MITBBS

Table 1. Discussion forums on MITBBS

Primary discussion forum category	Examples of specific forums under each category	No. of forums in each category
News	Overseas News, Business News, China News, Salon, etc.	32
Life	Living, Parenting, Food, Family, Money, Investment, etc.	50
Regional discussion	USA, Canada, Europe, and Australia, etc.	70
Sports and fitness	Football, Baseball, Swimming, Outdoors, and Travel, etc.	44
Entertainment	Music, Movie, TV, Gardening, Fashion, and Photo, etc.	43
Love and emotion	Dreamer, Lover, Les, Rainbow, and Piebridge, etc.	21
Literature	Arts, Chinese Classics, Comic, Poetry, and Prose, etc.	24
Alumni	Beijing University, Fudan University, Etc.	62
Hometown	Beijing, Shanghai, and Hubei, etc.	25
Computers and networking	Computer Science, Database, Linux, and Apple etc.	26
Academic disciplines	Business, Biology, Psychology, and Engineering, etc.	41
BBS system maintenance	Announcement, Complaints, and Tests, etc.	19
Clubs	A Variety of Clubs (Hobby, Technology, Games)	2000

user has a personal webpage which lists how frequently the user logged in, the number of comments posted and user status (e.g., regular user, system admin or forum host, etc.). Additionally and more importantly, MITBBS website offers information on performance measures such as *experience* and *activeness* (the dependent variables in our study). Second, data was collected on "social interaction". Social Network Analysis (SNA) was used to collect social interaction data from the Business discussion forum data sample and was used to analyze the related social structures. SNA uses network theory to analyze social networks and social relationships [17]. Relationships between participants such as friendship, kinship, organizations and sexual relationships are depicted in a "social network diagram" where nodes are represented as points and ties are represented as lines [17]. SNA is a distinctive methodology that encompasses techniques for data collection, statistical analysis and visual representation [14]. To analyze the interactive data from the MITBBS Business forum, the researchers followed a three-step procedure as detailed in Table 2 [16].

Step 1. Thread Downloads

The MITBBS website archives all threads posted since May 2001. Each thread may include more than one message (e.g., the original message and several replies to that message). Each message contains both the content and the sender of the message. The

Table 2. Social network analysis process

Steps	Summary	Software	Input	Output
Step 1. Threads download	Download all the threads from Business forum from May 2001 to May 2014	Web spider program[a]	Business forum on MITBBS	Threads with sender and replier
Step 2. Threads analysis	Generate a matrix revealing the interaction among users IDs (*i.e., who replied to messages from whom*)	Web parsing program[a]	Threads	Matrix showing interaction between each pair of user IDs
Step 3. Statistical analysis	Calculate network structure indices	Ucinet[b]	Matrix	Social network index indicator (e.g., *hierarchy*)

[a]Programs were developed by the author. [b]Software was developed by Borgatti et al. [9]

data was analyzed to determine the interaction between IDs, specifically, who sent message to whom. Starting from May 2001 to May 2014, there were approximately 5000 threads with over 30,000 messages posted by 350 different users. A web spider program was developed to download all these threads across 13 years, which then generated the data for our analyses.

Step 2. Thread Analyses

After threads were downloaded, the SNA process generates a matrix displaying the social interaction between each pair of user IDs. A Web parsing program was developed to produce the matrix as shown in Fig. 2. The rows and columns of the matrix

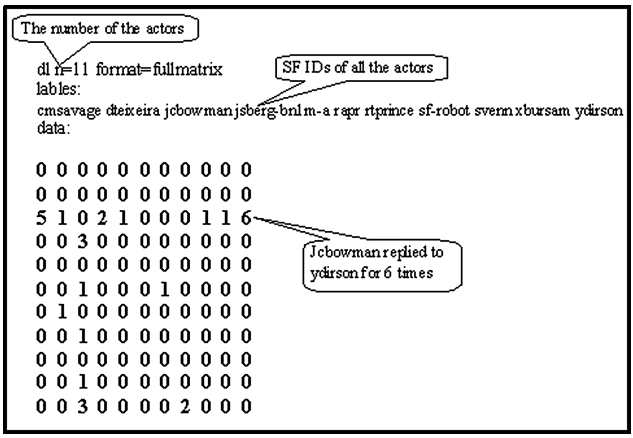

Fig. 2. An example of the generated matrix

represent participants in the social network, which are identified as the unique user IDs who posted messages on the MITBBS Business forum. The cells represent the interactions between each pair of IDs which are determined by the number of messages sent from row A to column B. The matrix is asymmetric since the reply message determines the direction; A may reply B more times than B replies A.

Step 3. Statistical Analysis

The matrices generated from step 2 served as input for the SNA software program. A SNA (see Fig. 3) was generated by UCINET [9], a widely-used software to measure and analyze social networks. A particular structural social network index such as "hierarchy" therefore, could then be calculated for each user ID to measure the structural hole for the ego index (i.e., the individual "focal" node) in this social network.

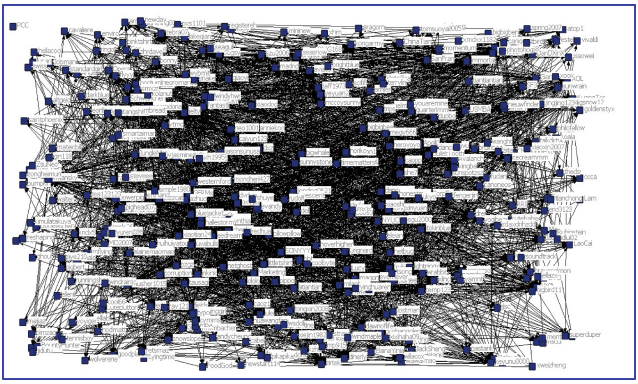

Fig. 3. Social network of the MITBBS; business forum for hierarchy variable

Individual Behavior and Performance

Once threads were downloaded and the user IDs who posted specific threads were identified, those user IDs were traced to their personal MITBBS homepage. Then two user IDs behavior measurements were gathered: the number of times that the user ID logged onto the website and the number of threads that particular user ID posted comments or replies. Two indices were then collected as indicators of performance: e*xperience* and *activeness.* Each performance indicator measures individual performance from different perspectives. As previously discussed, *experience* value focuses on the frequency or quantity of the messages the user ID posted on the website. *Activeness* is an indicator of the quality and frequency of meaningful posts and replies to queries by a user within a particular discussion forum. Table 3 shows a summary of the data collection and measurement procedures used for our analysis.

Table 3. Summary of data collection and measurement

Data type	Data source	Measurement
Online behavior (Login times, No. of posts)	Personal webpage	Content analysis
Social network (Hierarchy)	Threads from business forum	Social network analysis
Individual performance (Experience, Activeness)	Personal webpage	Content analysis

6 Results

Structural equation models were developed to test the research model depicted in Fig. 1. In assessing the research model, the Chi-square statistic (X^2), *p* values and the following fit indices were used: relative fit index (RFI), incremental fit index (IFI), Tucker-Lewis index (TLI) comparative fit index (CFI) and the root mean square error of approximation (RMSEA). Our initial structural model generated poor to moderate fit statistics and negative error variances. In cases where model refinement was required model paths were assessed and deleted one at a time and the fit of the refined model was reassessed, reflecting logical model building and purification [2, 10]. The final structural model (see Fig. 4) indicated no negative error variances and no unacceptable correlations (i.e., ≥1.00) [5]. Our final model generated good to very good fit indices (see Table 4) with a RMSEA of .044 which was below the recommended 0.10 threshold [4]. Standardized path coefficients from all independent variables (i.e., *login count, posts count, hierarchy*) to the two dependent variables, *experience* and *activeness* and were significant at $p < .05$.

As shown in Fig. 4, the path coefficient from *login count* to *experience* ($\beta = .24$) was significant at the $p < .05$ level. The path coefficient from *posts count* to *experience* ($\beta = .82$) was substantial and significant at the $p < .05$ level. The path coefficient from *posts count* to *activeness* ($\beta = .80$) was also was substantial and significant at the

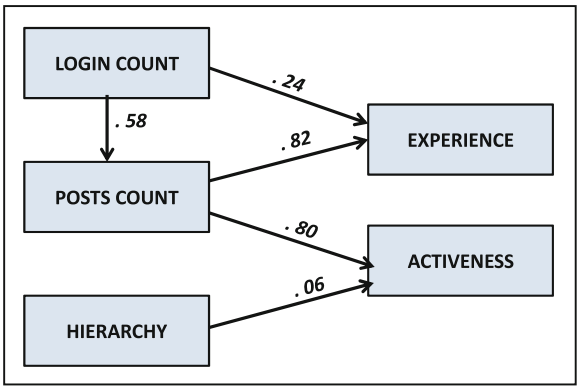

Fig. 4. Final structural model results

Table 4. SEM analysis result

Fit Statistic	(X^2)	*p* value	X^2/df	NFI	RFI	IFI	TLI	RMSEA
	8.335	.001	1.667	.995	.990	.998	.996	.044

$p < .05$ level. Finally, the path coefficient from *hierarchy* to *activeness* ($\beta = .06$) was significant ($p < .05$) but was not substantial. There was no relationship between *hierarchy* and *experience*. Our final structural equation model was stabilized by the addition of a path between Login Count and Post Count as these two variables we intrinsically related; *post count* could not occur without a user ID first logging (i.e., *login count*) into the MITBBS website.

7 Discussion of Results

Login count, which measures the number of times a user logs onto the MITBBS website, generated a significant relationship with *experience* but did not generate a relationship with *activeness*. This may be explained as follows. When a particular user accessed the MITBBS website numerous times it, of course, created a higher value for Login Count. Subsequently, the more frequently a user accessed a social media website, the more familiar the user became with the website features of that particular virtual community, thus creating a higher "experience" value. However, merely logging in and cruising a particular social media website did not guarantee that a particular user also posted replies to queries or created discussion threads which would increase the "activeness" value of the user.

Posts Count generated a significant and substantial relationship with both *experience* and *activeness*. This may be explained as follows. A higher post count would assume at least a minimum frequency of login count (hence the relationship between login count and post-count in Fig. 4). That is, if a user logged in numerous times and also posted numerous replies to queries and discussion threads, that particular user would generate both a high a higher experience value and a higher activeness value. Conversely, as a user would post more replies and initiate new discussion threads it would be logical that the user would become more familiar with the features of that particular discussion forum. Subsequently, the user would create a higher probability of posting more replies to queries and generating quality discussion threads thus, generating a higher *activeness* value.

Hierarchy, as a measure of structural hole, indicates whether structural constraints are concentrated on certain users or is evenly distributed among other users. As previously discussed, the higher the value of hierarchy, the more unequal the strength of the relationships distributed across a particular social network, creating a greater probability that new information and will more easily diffuse among the heterogeneous participants. Hierarchy generated a positive relationship with *activeness*. However this relationship was not substantial. This may be explained as follows. *Activeness* as previously defined is the quality and frequency of meaningful posts and replies to queries and threads from other users [16]. Activeness may be influenced by the diversity of user information (i.e., hierarchy) and *hierarchy* may be affected by other

factors such as user personal user traits. While the heterogeneous information (received from a unevenly distributed network) may have exposed the user to new information, it may not have been substantial enough for the user to feel empowered to further share (i.e., post) this new information with others in his social media network.

However, this same dynamic did not apply to the relationship between hierarchy and experience. *Hierarchy* did not generate any relationship with *experience*. This may be explained as follows. Since the relationship between hierarchy and activeness was already low, we could assume that the frequency of user posts that shared new information with other users was also low. Subsequently, the availability of new, heterogeneous information may not have affected the relative experience value of the user who may have been accessing or cruising a particular website without posting replies, disseminating knowledge or creating discussion threads.

8 Implications for Future Research

The results of our research emphasize the value of maintaining heterogeneous networks outside an immediate social media group. Participants that are connected across a span of different social media groups are exposed to alternative sources of new knowledge which generates social capital [7]. The greater the number of weak links or structural hole connections between these heterogeneous social media groups, the more diverse new information may be linked to various groups and individuals thus generating new ideas, knowledge and social capital.

Our research results generated several implications for future research studies. First, the analysis of other structural hole factors such as density, centrality, and core/periphery could provide researchers with different perspectives on the social structure characteristics of social media networks. These factors could influence social capital and individual performance. Second, studying the effects of different structural hole factors could be compared across different discussion forum categories (see Table 1). As previously stated MITBBS hosts hundreds of different discussion forums. For the current study, data from the Academic-Business category provided a casual social media community that discussed issues relating to the business discipline in general. Social media network data from other discussion forums which focus on sharing new ideas and innovations could provide different results. Finally, future research studies could analyze data from entirely different social media outlets (e.g., Facebook, Twitter, LinkedIn) to test how different social structural factors within different social media networks affect social capital and individual performance.

9 Conclusion

This research investigated the relationship between the effect of one structural hole factor (*hierarchy*) on the creation of social capital and its effect on individual performance within a social network. Our results indicate that while the frequency of user Logins (i.e. *login count*) affected the *experience* value of individual performance, it did not affect the *activeness* value of individual performance. Conversely, the number of

posts (i.e. *posts count*) submitted by a particular user significantly affected both the *experience* value and the *activeness* value of individual performance. Finally, *hierarchy* (as a measure of structural hole) generated a small relationship with the *activeness* value but no relationship with the *experience* value. Our research results suggest the possibility that connections or weak links with heterogeneous groups or other individuals outside of a particular social network media group may facilitate the generation of new ideas and useful knowledge. We encourage future research in this direction.

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