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HOW THE SOCIAL CAPITAL EFFECTS KNOWLEDGE SHARING WITHIN A SOCIAL NETWORK -- A RESEARCH BASED ON ZHIHU

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ABSTRACT

Based on an integrated theoretical perspective of knowledge sharing behavior, social capital and social network, this paper proposed a model illustrating that the knowledge sharing effectiveness in a social network is influenced by three dimensions of social capital. And then an empirical research is conducted among the users of Zhihu which is a social network specialized in knowledge sharing based in China. Based on 354 valid questionnaires obtained through data capture approach within Zhihu, the social network analysis technology and regression analysis are jointly employed to explore the relationship between social capital and knowledge sharing effectiveness. The results show: the quality of knowledge sharing is positively related to social capital structure, whereas the quantity of knowledge sharing hardly; the quality of knowledge sharing is positively related to cog-nition; trust, community recognition significantly affect the quality of knowledge sharing, while mutual benefit has no significant influence on it; reciprocity, community recognition and knowledge sharing is positively correlated, but trust has no significant effect on knowledge sharing

Keywords: Social capital; Social network; Knowledge sharing; Zhihu

INTRODUCTION

The social network has become a widely-used channel for the broad masses to exchange information and share knowledge, communication through which is regarded as an effective way for knowledge sharing and spreading. Despite the wide adoption in reality, there still remain quite a lot of controversies on some theoretical and managerial issues, the interactive mechanism between social network and knowledge sharing, the management rules, formalized or non-formalized, on social network aiming to promote knowledge sharing, etc..A common practice is to introduce a kind of antecedents, namely social capital, into the study to observe the evolution process of knowledge sharing(Amayah T. 2013). As a product of the individual interaction, social capital bears great influences on individual behavior, especially in the circumstance of Internet popularity, where the individual interactions transfer from offline to online. On the other hand, the social capital, resulted from social-internet individual interaction, has showed some new properties (David F. Nettletona, Julián Salas. 2016). Due to the exposure to the network properties, such as the relation intensity, reciprocity, and identification, the definition and measurement of social capital, as well as the working mechanism on knowledge sharing, showed some new characteristics. However, the existing research on these new attributes and features has not yet reached a consistent conclusion (RichelleMayshak, Stefanie J. Sharman, LucyZinkiewicz. 2016).We tend to start with the definition of social capital respectively in structural, cognitive, and relational dimensions, then explore the possible influence on knowledge sharing in the network, and analyze the possibility of mutual interference in the above-mentioned process(Heaphy D., Dutton E. 2008; Zhijun Yan et al. 2016). This paper also aims to provide relevant implications in decision-making for both supervisors and managers with the expectation to contribute to the spread of knowledge sharing and promote the formation of virtuous social trust.

2 Hypothesis and conceptual modeling

Social capital is usually defined as inheres in the relations between and among persons and is a productive asset facilitating some forms of social action while inhibiting others, rooting in three dimensions: structural, cognitive and relational (Nahapiet J, Ghoshal S. 1998). The structural dimension is characterized by network ties, network configurations and appropriable organizations. The cognitive facet includes shared codes and languages, and shared narratives. The relational dimension is shaped by trust, norms, obligations, and identification. Social capital exerts influences on the knowledge sharing among social network through the above –mentioned dimensions.

2.1Structural dimension and knowledge sharing

As knowledge sharing in a social network are collective activities, the linkage between and among the members, or the network ties resulted from these ties and be employed to forecast the collective activities (Tsai W, Ghoshal S. 1998). Collective activities are more liable to occur in a social network of heavier intensity and higher interactive frequency (David Kempe, Jon Kleinberg, EvaTardos. 2015). Frequent communication among individuals more likely leads to a cooperation routine and collective activities(Kim B. 2013). One of the aims an individual participate collective activities lies in acquiring identification and dignity, thus improving personal position in the network might produce the centrality.

Centrality means the relevant location of participants in a social network. As a variable measuring structural social capital, centrality in a social network is closely linkedto knowledge sharing. As far as collective activities are concerned, the member of higher position and stronger centrality is more willing to participate than the one with lower centrality, and participant with higher centrality is more likely to understand and comply with the rules and routines in a network (Chai S, Das S, Rao H. 2011). The individual position in the social network will affect the knowledge sharing to others, therefore the centrality can be measured by the number of social ties with other members in the social network (Henttonen K, Janhonen M, Johanson J E. 2013). In this article, point-degree centrality, namely the members directly linked to a specific individual, is employed to evaluate the personal centrality. More direct linkage presumably suggests a stronger centrality, thus more identification and dignity from other members, and more likely influence on knowledge sharing among the network.

Based on the above analysis, this paper puts forward the following assumptions:

H1a: centrality imposes a positive effect on the quality of knowledge sharing

H1b: centrality imposes a positive effect on the quantity of knowledge sharing

2.2 Cognitive dimension and knowledge sharing

Cognitive capital includes common language and shared vision. As a way of communication among people, language can reflect a person's professional knowledge. Common language and communication bring great convenience in the process of reaching a collective goal in the social network (Casimir G, Lee K, Loon M. 2013).Meaningful communication requires at least some common understanding of vocabulary and knowledge (Borges R. 2012), for example, users of cartoon and animation website will share some jargon or technical terms, and the user coming from a same area will communicate with their local dialects. Common language is essential for knowledge sharing in a social network, it enables the participants to understand each other and create a common vocabulary for communication. Common language not only helps to share ideas, also improves communication efficiency among the members with similar background and experience. Therefore, common language will help motivate active participation in knowledge exchange activities and improve the quality of knowledge sharing in the social network.

Based on the above analysis, this paper puts forward the following assumptions:

H2a: common language imposes a positive effect on the quality of knowledge sharing

H2b: common language imposes a positive effect on the quantity of knowledge sharing

Shared vision is considered as an integration mechanism among different resources, usually embodies the collective goals and common wishes in an organization (Yong Sauk Haua, Minhyung Kang 2016). Members sharing a common vision are more likely to exchange and

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share resources (Zaqout F, Abbas M. 2012).Shared values and goals will bring the network members together, enable cooperation and further development of organization(Wasko M L, Faraj S. 2005). Within a certain social network the participant communicates with each other based on common interests, goals or objectives, which makes the exchange of information and knowledge between members possible, the knowledge sharing between members meaningful, and promotes the quality and quantity of knowledge sharing.

Based on the above analysis, this paper puts forward the following assumptions:

H3a: shared vision imposes a positive effect on the quality of knowledge sharing

H3b: shared vision imposes a positive effect on the quantity of knowledge sharing

2.3 Relational dimension and knowledge sharing

Relational capital provides convenience for communication activities. When relational capital exists in a group, members have a strong sense of identification, trust on the others in the group, liability to participate, and willingness to abide by the cooperation rules (Chiu M, Hsu H, Wang G. 2006). Relational capital incorporates three main facets: trust, reciprocity and community recognition. In single-dimension stage, trust is considered the only measure on social capital. Trust refers to a sort of expectation of activities in accordance with common values, norms and principles (Ping Liang,ZhongLiyong 2010), High degree of trust among members presumably promotes cooperation and sharing (Babar A, Verner M, Nguyen T. 2007).Within a trust relationship, concerns on betrayal of privacy and chances of taking advantages will reduce considerably, and more willingness to cooperate will produce (Zachary Neal. 2015). Interpersonal trust plays a quite important role for a team or organization by creating an atmosphere of knowledge sharing (Babar A, Verner M, Nguyen T. 2007). As an informal communication, where individual contribution is difficult to assess, knowledge sharing highlights the importance of trust in social network. Trust can create and maintain good exchange relationship, consequently, guarantees the quality of knowledge sharing (Nonaka I. 1994).

Based on the above analysis, this paper puts forward the following assumptions:

H4a: trust imposes a positive effect on the quality of knowledge sharing

H4b: trust imposes a positive effect on the quantity of knowledge sharing

Reciprocity refers to that the two parties uphold the principle of fair exchange, share knowledge to others with the expectation the counterpart would positively share in return (Yalan Yan,XianjinZha, Ming Yan. 2014). Reciprocity means an expectation on other people to respond actively, versus, once participant find the desire cannot be implemented, the knowledge sharing behavior will be stopped (MihailCocosila, Andy Igonor2015).The theory of social exchange suggests that the participant of knowledge sharing expect equivalence in their time and effort being shared as a return (Davenport H, Prusak L 1998).Members will claim rewards when sharing knowledge to others out of a sense of fairness and incentives. The members only acquiring or benefiting from knowledge share, and not responding positively by sharing to others, will inevitably face pressures of mutual-beneficial norms (Bagozzi P, Dholakia M. 2002).In the intellectual market, reciprocity works as an incentive to knowledge sharing.

Based on the above analysis, this paper puts forward the following assumptions:

H5a: reciprocity imposes a positive effect on the quality of knowledge sharing

H5b: reciprocity imposes a positive effect on the quantity of knowledge sharing

Community recognition is usually defined as a sense of identity to the own collective, thinking oneself as a part of the collective (Wei-Li Wu, Yi-Chih Lee. 2016). Recognition is a personal experience one thinks himself belonging to a group (ChenyanXu,Sherry Ryan,Victor Prybutok, ChaoWenb 2012).In a social network, the recognition, to some extent likes an emotional identification, is defined as a sense of belonging to a specific social network sites one uses frequently. Emotion identification in a social network can help to build loyalty and code of conduct, cultivate willingness to pay efforts jointly to build a community and maintain a benign relationship with other members (Chen J, Hung H. 2010). Community recognition can function as stimuli to knowledge exchange, low recognition within a community will constitute a severe barrier against information sharing, learning, and knowledge creating (Andrew Parker, Daniel S. Halgin,Stephen Borgatti.2016).Since social network sites exist online rather than by entities, members are linked together by common interests or together appeals. Usually the valuable knowledge exists in one's mind, and people intentionally protect their own knowledge, so unless other members have been regarded as trustworthy, one should not be willing to contribute the personal knowledge. Therefore, community unity and solidarity will promote the sharing activities, and benefit the breadth and depth of knowledge sharing.

Based on the above analysis, this paper puts forward the following assumptions:

H6a: Community recognition imposes a positive effect on the quality of knowledge sharing

H6b: Community recognition imposes a positive effect on the quantity of knowledge sharing

The concepts and hypothesis are illustrated in the following model:

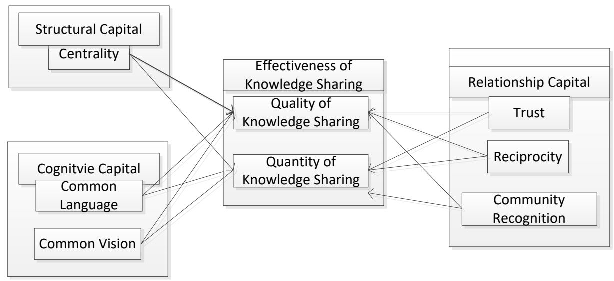

Figure1 Conceptual Model in this Article

3 Research Design

3.1 ResearchObject

Relatively Interest in social networks typically includes four kinds of platform in China: interest-oriented, media-oriented, relation-oriented, and question-and-answer. Since the knowledge sharing effects in the above platforms all show reasonable relevance to network-structure and social capital embedded in the network, the selection among the kind of platform will make rare difference. As a typical question-and-answer platform in China, Zhihu launched in 2011 as a start-up firm, initially adopting the invitation mechanism for registration, aiming to select seed-users, build a high-quality UGC (User Generated Content) and cultivate a friendly knowledge sharing atmosphere. In 2013, Zhihu opened registration, which resulted in a dramatic surge of users to 17 million from then on. Now Zhihu almost has covered all areas of subject, allowing users to inquire what they are interest in or to answer to what they are familiar with. Furthermore, the user in Zhihu can establish social relationships with others through the focus-on-mechanisms. All above-mentioned mechanisms help to achieve a high-degree knowledge sharing.

The main reasons why this paper selected Zhihu as the research object lies in three aspects: the first is this firm provides professional solutions to deal with complicated knowledge flow. Zhihu intentionally invited professionals in various fields early on the seeding stage aiming to lay a solid and specialized knowledge foundation. As to knowledge sharing, this firm also has comparative advantage over other social platform when measuring the characteristics of rationality, objectiveness and reasonability. Secondly, the users provide variety of perspectives whether asking or answer questions. Even some experts specialize in certain field prefer to gathering on Zhihuto explore some frontier issues, which enable multi-perspective interpretation on an identical problem, and ensure the comprehensiveness, diversity and equality of knowledge sharing. Thirdly, the users' average willingness of knowledge sharing is stronger than other firms'. The identity of Zhihu itself as a question-and-answer platform shapes its mission of solving problems and acquiring knowledge. The user who provides more high-quality answers will be much better recognized by the network and gain more popularity, which further promote the willingness of knowledge-sharing. Additionally, this firm pays its most effort to establish principle of reciprocity, so, even for the knowledge-seekers, access to high-quality of knowledge will promote their feedback.

3.2 Variables definition and measure

Structural dimension of social capital is mainly manifested by centrality. Centrality refers to the users' position in the social network, more central the location, richer the resources possessed (PeymanAkhavan, Mahdi Hosseini 2015). In this paper, absolute point-degree centrality is adopted to measure the variable of centrality, which is manifested by the number of points directly connecting to a specific node in a social network. Data capture software is used to obtain the initial data describing the relationship among specific users on Zhihu platform, and network analysis tools are used to calculate the network centrality. The measure on structural dimension is not included in the scales and questionnaire.

Cognitive capital includes two facets: common language, and shared vision. Common language means communication can be carried out with mutual-understood, mutual-recognized language, and shared vision refers to consistent goals and desires. Based on the existing research, this paper puts forward six metrics measuring cognitive capital (Tobias Bohmelt, JurgVollenweider (2015), as shown in table1. Relational capital incorporates three dimensions: trust, reciprocity, and community recognition. Trust promote the liability to believe the other members will abide by universally applicable rules in the virtual community; Reciprocity means the corresponding reward in the knowledge exchange; Community recognition refers to a positive identification and a sense of belonging in a virtual community (Chenyen Yao, ChinchungTsai,Yenchiang Fang 2016). 17 questions are put forward to measure the relational capital, as shown in table1 below:

Table1 Measures on cognitive capital and relational capital

dimensions	variables	measuring questions
cognitive	common	Col 1 I think users on Zhihu will use common

capital		terminology and jargon
	language	Col 2I think users on Zhihu can communicate effectively
		Col 3I think users on Zhihu ask and answer questions in an understandable style
	shared vision	Shv 1I think users on Zhihu uphold a belief of helping to solve problems professionally
		Shv 2I think users on Zhihu share a common vision of co-learning
		Shv 3I think users on Zhihu hold common value, and are willing to offer
relational capital	Trust	Tru 1I think users on Zhihu will not take advantage of others even if a chance
		Tru 2I think users on Zhihu will keep their promise
		Tru 3I think users on Zhihu will not interrupt a conversation intentionally
		Tru 4I think users on Zhihu behavior in a consistant way
		Tru 5 I think users on Zhihu will communicate with others sincerely
	reciprocity	Nor 1 I believe I am obliged to offer helps because I know they will help me when I need
		Nor 2 I believe the members on Zhihu will offer a hand when I am in need
	community recognition	Ide 1 I can find a sense of belonging on Zhihu
		Ide 2 I can find a feeling of closeness

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		Ide 3 I am fond of Zhihu very much
		Ide 4 I am proud of being a member of Zhihu

Knowledge sharing effectiveness is illustrated by quality and quantity jointly. The quality of knowledge sharing refers to the value and usefulness of the knowledge shared; Quantity refers to the number of answers from the members (Carol Ou, Robert Davison, Louie Wong2016). Based on previous studies, 7 measuring items are used to evaluate the knowledge sharing effectiveness, as shown in the table 2:

Table 2 Measures on the knowledge sharing effectiveness

variables	**measuring questions**
quality of knowledge shared	Qual 1 I believe the knowledge shared on Zhihu is relevant to the specific subject
	Qual 2 I believe the knowledge shared on Zhihu is easy to understand
	Qual 3 I believe the knowledge shared on Zhihu is accurate
	Qual 4 I believe the knowledge shared on Zhihu is intact
	Qual 5 I believe the knowledge shared on Zhihu is reliable
	Qual 6 I believe the knowledge shared on Zhihu is timely
quantity of knowledge shared	Quan 1 the average amount of posts per month

3.3 Design and adjustment of pre-test questionnaire

3.3.1Design of pre-test questionnaire

The questionnaire in this study is divided into two parts, the first part is the respondent's personal information on Zhihu, including gender, age, profession, level of education, period of use, frequency and average period of each use. The second part is the scales, including 7 variables in the conceptual model: trust, reciprocity, community recognition, common language, shared vision, the quality and quantity of knowledge shared. 5 Likert scale is employed to measure in the scales, in which 1 means completely disagree, and 5 completely agree.

3.3.2 Pre-test and adjustment of questionnaire

The questionnaire should be pre-tested before it is used formally. The pre-test was conducted on SOJUMP, a specialized survey website, and a total of 150 questionnaires were issued. Excluding invalid questionnaire, the response time too long (more than 500 seconds) or too short (less than 90 seconds), finally 143 valid questionnaires were recovered, with the recovery rate of 95.3%.

When conducting the Cronbach's alpha testing using SPSS20.0, the results showed that, for variable "trust", the CITC values of Tru4 and Tru5 are both less than 0.5, the Cronbach's alpha improved after deleting them. So Tru4 and Tru5 were deleted from the scales; Based on the same reason, the items Qual1 and Qual2for “quality of knowledge sharing" variables were deleted too. CITC values of items for the other variables were all above 0.5, and the overall Cronbach's alpha value is greater than 0.7 in the adjusted questionnaire, which means a good credibility. Furthermore, exploratory factor analysis has been carried out on the rest of the 19 items , the results showed KMO test value of 0.904, and Bartlett sphere test showed the approximate chi-square value of 4509.79, the freedom degrees of 171, the significant probability $p = 0.000 < 0.01$. 6, common factors are extracted from 19 items, and eigenvalues are all greater than 1. The load in the related factor all exceeds 0.5, the adjusted questionnaire scale shows good structural validity.

3.4 Data capture and formal questionnaire

We limit data-collection and object-investigation within Zhihu.During data collection, Python language is used to edit the Crawler-Program to capture data. Start with the node where the big-V-users (verified users who have much more influence than others within the social network) are located, trace the members the big-V-users pay attention to, and capture the data according to the principle of breadth-first, finally data is obtained with snowball-sampling-method. The strategy on capturing personal homepage data is to select influential users as seeds, and then spread out the capture in the form of a tree. Specific process is as follows:

Step 1, Select the top ten user on Zhihu Rank as the seed-URL, list them on the “to-be-captured” , and set the total number of captured pages; Step 2, Capture the data on the “to-be-captured” list in turn, DNS process is used to remove a page on the “to-be-captured” list, connect this page, download URL corresponding page (i.e. Zhihu personal information page), and verify whether the page has been captured. If not, go onto step 3, if yes, back to step 1; Step 3,With the python program, obtain the data of amount of concerned users, amount of fans, ID and personal-information URL of concerned user, ID and personal-information URL of fans, then put the obtained concerned-user URL and fans URL to the end of the “to-be-captured “list; Step 4. Repeat step 2-3, until reach the set amount of captured pages or exceed the set time limit.

When we capture the user data with crawlers-program, the questionnaires are sent to them via personal message aiming to investigate the influence social capital, exclusive structural dimension, exerted on knowledge sharing. The users who reply the messages and return questionnaires will get their access to our formal investigation. 450 questionnaires have been issued on October 7, 2015, and 375 have been recovered till December 7, 2015. Finally, 354 valid questionnaires are collected.

3.5 Analysis on relationship matrix and description on central degree

On Zhihu, user's home page includes a variety of content plates: the amount of the users concerned, the amount of fans, the "answer", the "question", focusing topics, etc. The data of “the amount of users concerned” and “the amount of fans” is captured and stored into an Excel table, as the original data to analyze user centrality. Before processing the data, we code each user first in order to facilitate further analysis. The starting node is coded as 1 and then coded 2,3,4,5, along with the trace of snowballing. A relation matrix of 354 x 354 is establishedin the Excel table to determine the relationship among the users. Table 3 shows part of the relationship matrix:

Table3Part of the Relationship Matrix

	1	2	3	4	5	…	351	352	353	354
1	0	0	0	0	0	…	1	0	0	0
2	0	0	0	1	0	…	0	0	0	0
3	1	0	0	0	0	…	0	0	0	0

4	0	0	0	0	0	…	0	0	0	0
5	0	1	0	0	0	…	1	1	0	1
6	0	0	0	0	0	…	0	0	0	0
7	0	0	0	0	0	…	1	0	0	1
…	…	…	…	…	…	…	…	…	…	…
351	0	0	0	0	1	…	0	1	0	1
352	1	1	0	1	0	…	0	0	0	0
353	1	1	0	1	0	…	0	0	0	0
354	0	0	0	0	0	…	0	0	0	0

A figure of social network relational community, drawn by Netdraw, can vividly show the relationship among the users investigated:

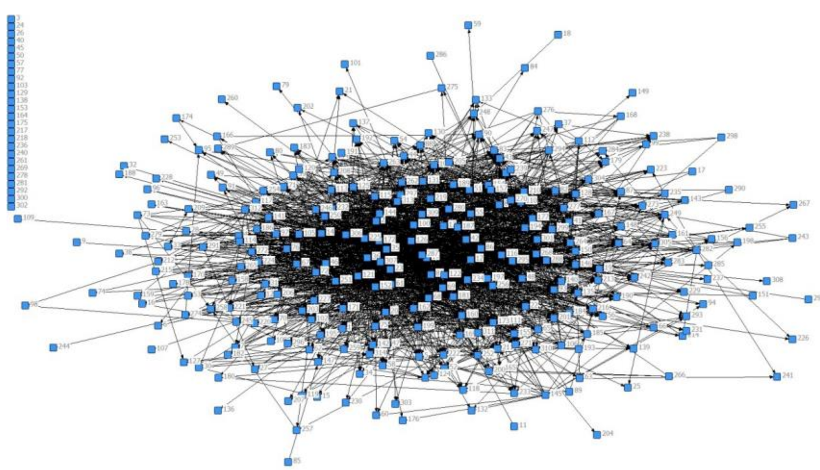

Figure 2 Relational Community on Zhihu

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Centrality is an indicator of the user's position in a social network which is illustrated with the metric point-degree centrality in this paper. Point-degree centrality is divided into point-in-centrality and point-out centrality. The point-in degree is measured by the number of fans owned by users, and the point-out degree is measured by the number of users concerned. In this paper, we use the UCINET software to analyze the centrality. The network orientation of the samples is not preserved in the analysis. The absolute centrality of the samples is shown in table 4:

Table 4 Descriptive Statistic Analysis on Point-Degree Centrality

	Degree	NrmDegree
Mean	16.866	5.389
StdDev	21.504	6.870
Sum	5296.000	1692.013
Variance	462.402	47.199
Minimum	0.000	0.000
Maximum	115.000	36.741

Network Centralization= 31.55%

Point-degree centrality of a portion of samples is shown in Table 5:

Table 5 Point-degree Centrality of Part of Samples

	Degree	NrmDegree
12	115	36.741
225	105	33.546
23	104	33.227
……………………………………………		
287	102	32.588
306	94	30.032
35	88	28.115
……………………………………………		
40	0	0
236	0	0

According to Table 5, node 12 has the highest absolute point-degree centrality rather than the starting node 1, which shows the starting node is not necessarily in the center of the network. In the network containing 354 nodes,115 nodes have been observed directly related to node 12.

4 Data analysis and discussion

In this chapter, empirical analysis was carried out on data collected from the formal questionnaires, including descriptive statistics analysis, reliability and confirmatory factor analysis on the sample data, correlation analysis and multiple regression analysis on the conceptual model, and the hypothesis will be tested according to the analysis results.

4.1 Descriptive statistical analysis

We recovered 354 effective questionnaires in this study, the recovery rate 78.67%. The descriptive statistical analysis has been carried out on the demographic characteristics of the population in the questionnaire samples. The results show that 50.8% of respondents are male and 49.2% female. The other personal characters, age, level of education, professionality distribute decentralized; Most of the respondents have used Zhihu for a long period of time, had a deep understanding to it and expressed a pleasant experience on Zhihu. According to the analysis results, all the items score in a range of 1 to 5(including 1 and 5), suggesting a reasonable degree of distinctiveness. The mean value for each item distributes equilibrium, around 3, and standard deviation ranges between 0.8 and 1.1, suggesting a reasonable discrete degree.

4.2 Questionnaire reliability and validity analysis

To analyze reliability and validity of questionnaire, this paper employed SPSS20.0 to calculate CITC values and Cronbach's alpha coefficient, while Amos17.0 to do confirmatory factor analysis (CFA). As shown in Table 6, the goodness of fit proves to be in good condition.

Table 6 the Goodness of Fit on Confirmatory Factors

metrics	df	χ^2 value	χ^2/df	p value	RMSEA	NFI	CFI	IFI
value	171	452.849	2.648	0.000	0.084	0.902	0.930	0.930

Table 7 shows reliability and validity of the questionnaire. Where CITC value of each item is greater than 0.5, and Cronbach's alpha coefficient of each variable is above 0.8, which means the data has acceptable liability. In addition, the factor loading of each item is greater than 0.5, and reaches significant level, so the data has good convergent validity.

Table 7 Reliability and Validity of the Questionnaire

variables	items	factor loading	t-value	P	Corrected item total corellation (CITC)	Cronbach's Alpha value when item deleted	Cronbach's Alpha value
trust	Tru1	0.86	13.092	***	0.632	0.875	0.849

	Tru2	0.902	17.014	***	0.78	0.731	
	Tru3	0.68			0.749	0.759	
reciprocity	Nor1	0.82	15.365	***	0.746	-	0.854
	Nor2	0.83			0.746	-	
community recognition	Ide1	0.831	17.178	***	0.766	0.878	0.901
	Ide2	0.817	18.436	***	0.815	0.86	
	Ide3	0.867	16.929	***	0.763	0.879	
	Ide4	0.825			0.775	0.874	
common language	Shl1	0.707	13.591	***	0.708	0.88	0.879
	Shl2	0.724	12.366	***	0.806	0.791	
	Shl3	0.797			0.785	0.811	
shared	Shv1	0.882	16.675	***	0.73	0.791	0.854
vision	Shv2	0.872	20.648	***	0.727	0.794	
	Shv3	0.769			0.719	0.802	
quality of knowledge shared	Qual3	0.826			0.778	0.851	0.89
	Qual4	0.852	17.177	***	0.809	0.838	
	Qual5	0.812	16.178	***	0.774	0.852	
	Qual6	0.702	13.357	***	0.674	0.889	

4.3 Correlation analysis

Correlation analysis had been carried out respectively between structural capital, cognitive capital, relational capital and knowledge-sharing effects.

Table 8 Correlation Analysis between Main Variables

		quality of knowledge sharing	quantity of knowledge sharing	trust	reciprocity	community recognition	common language	common vision	centrality
quality of knowledge sharing	pearson correlation	1							
	significant(two-tailed)	-							
	N	354							
quantity of knowledge sharing	pearson correlation	0.618**	1						
	significant(two-tailed)	0	-						
	N	354	354						
trust	pearson correlation	0.623**	0.525**	1					
	significant(two-tailed)	0	0	-					
	N	354	354	35					

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				4					
reciprocity	pearson correlation	0.609**	0.596**	0.700**	1				
	significant(two-tailed)	0	0	0	-				
	N	354	354	354	354				
community recognition	pearson correlation	0.661**	0.610**	0.673**	0.649**	1			
	significant(two-tailed)	0	0	0	0	-			
	N	354	354	354	354	354			
common language	pearson correlation	0.663**	0.668**				1		
	significant(two-tailed)	0	0				-		
	N	354	354				354		
common vision	pearson correlation	0.717**	0.674**				0.767**	1	
	significant(two-	0	0				0	-	

	tailed)								
	N	354	354				354	354	
centrality	pearson correlation	0.387^{**}	0.362^{**}						1
	significant(two-tailed)	0	0						-
	N	354	354						354

The Pearson correlation coefficient matrix in Table 8 indicate that centrality and knowledge sharing effectiveness, including quality and quantity, is positive correlated; Three variables in relational capital, trust, reciprocity, community recognition, and two variables in the effectiveness of knowledge shared, the quality of knowledge shared and quantity of knowledge shared are positive correlated respectively. The analysis suggest a good correlation between the main variables, and suitable for further regression analysis.

4.4 Regression analysis

4.4.1 Regression Analysis between Social Capital and Quality of knowledge sharing

Employing quality of knowledge sharing as the dependent variable, centrality, common language, shared vision, trust, reciprocity, community recognition as independent variable, a multiple regression analysis produce the results in table 9:

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Table 9 the Regression Analysis Results

input varables	non-standard coefficient		standard coefficient	t	significance	collinearity	
	B	standard erro	β			tolerance	VIF
constants	0.879	0.126		6.966	0		
shared vision	0.313	0.054	0.36	5.751	0	0.336	2.976
community recognition	0.204	0.046	0.243	4.425	0	0.437	2.286
common language	0.14	0.056	0.151	2.5	0.007	0.363	2.754
trust	0.116	0.053	0.12	2.203	0.028	0.444	2.255
centrality	0.074	0.036	0.096	2.051	0.041	0.599	1.669
model	R	R-square	adjusted R-square	estimated standard deviation	change statistics		
					R-square change	changed F	
	0.774e	0.599	0.592	0.4871	0.005	0.041	

a. dependent variable: quality of knowledge sharing

According to Table 9, the regression model of tolerance ranged from 0.336 to 0.599, VIF did not appear to a value greater than 10, indicating that there is nomulticollinearity existed among the pre-tested variables. 59.9% explained-variance and the significant probability of variance increase p=0.041<0.05 suggest good regression effect. The coefficients in Table 9 showed that H1a, H2a, H3a, H4a and H6a have been verified, there existed respectively significant positive correlations between knowledge sharing quality and centrality, common language, shared vision, trust and community recognition respectively; but reciprocity was not significantly related to knowledge sharing quality, so H5a is denied.

4.4.2 Regression Analysis between Social Capital and Quantity of knowledge sharing

Employing quantity of knowledge sharing as the dependent variable, centrality, common language, shared vision, trust, reciprocity, community recognition as independent variable, a multiple regression analysis produce the results in Table 10:

Table 10 the Regression Coefficients and Significance Analysis

input variables	non-standard coefficient		standard coefficient	t	significance	collinearity	
	B	standard erro	B			tolerance	VIF
constant	0.196	0.182		1.077	0.282		
shared vision	0.303	0.077	0.263	3.948	0	0.334	2.998
common language	0.299	0.081	0.243	3.69	0	0.342	2.928
community recognition	0.215	0.061	0.194	3.534	0	0.493	2.028
reciprocity	0.143	0.059	0.138	2.421	0.016	0.454	2.202
Model	R	R-square	adjusted R-square	estimated standard deviation	change statistics		
					R-square change		changed F
	0.736d	0.541	0.536	0.686	0.009		0.016

a. dependent variables: quantity of knowledge sharing

The regression model of tolerance lied between 0.334 and 0.493, VIF did not appear to a value greater than 10, indicating that non multicollinearity existed among the predictive variables. The combined explained -variance of common language, shared vision, reciprocity and community recognition being 54.1% and the significant probability of variance increase p=0.016<0.05 suggested good regression effect. The coefficients in Table 10 showed that H2b, H3b, H5b, and

H6b have been verified, there existed respectively significant positive correlations between knowledge sharing quantity and common language, shared vision, reciprocity and community recognition respectively; but trust and centrality were not significantly related to knowledge sharing quantity, so H1b and H4b are denied.

4.5 Hypothesis testing results and discussion

The hypothesis testing results are concluded as in Table 10.

Table11Results Hypothesis Certifying

hypothesis	contents	results
H1a	centrality imposes a positive effect on the quality of knowledge sharing	valid
H1b	centrality imposes a positive effect on the quantity of knowledge sharing	invalid
H2a	common language imposes a positive effect on the quality of knowledge sharing	valid
H2b	common language imposes a positive effect on the quantity of knowledge sharing	valid
H3a	shared vision imposes a positive effect on the quality of knowledge sharing	valid
H3b	shared vision imposes a positive effect on the	valid

	quantity of knowledge sharing	
H4a	trust imposes a positive effect on the quality of knowledge sharing	valid
H4b	trust imposes a positive effect on the quantity of knowledge sharing	invalid
H5a	reciprocity imposes a positive effect on the quality of knowledge sharing	invalid
H5b	reciprocity imposes a positive effect on the quantity of knowledge sharing	valid
H6a	community recognition imposes a positive effect on the quality of knowledge sharing	valid
H6b	community recognition imposes a positive effect on the quantity of knowledge sharing	valid

As for H1b, we assumed that centrality has a positive effect on the quantity of knowledge sharing in this paper, but the regression analysis results indicate otherwise. The reason presumably lies that, the randomly selected objects in our study are only general members of the network, having a relatively low-centralized position in the network, so the data analysis of the acquired centrality from data analysis have smaller influence on the quantity of knowledge sharing. Existing research have shown that a member with higher centrality care more about the quality and quantity of knowledge sharing in order to maintain their position in the network, while the low centralized members mainly aim to seek information when entering a social network (Michele Mautheet al.2015), they give more priority to browse answers from the network, and receive the shared knowledge, and pay little attention to the quantity of knowledge sharing.

The regression analysis suggest H4b invalid, which means trust has no significant impact on the quantity of knowledge sharing. It is possibly due to that, people are willing to share knowledge because of the close and frequent interaction between members, the fairness of the knowledge exchange and the positive feelings on social network, rather than the trust among social network members (Zachary Neal. 2015). Another possible reason is that there is no perceptive risk when sharing knowledge in the context of confidential relationship, in another word, trust might be more necessary if actors believe themselves in a risky situation.

This paper assumed that reciprocity has a positive effect on the quality of knowledge sharing in this paper, as H5a, but the regression analysis results indicate otherwise. The reason probably lies in that, knowledge sharing of reciprocity is not a simple relationship, that is to say, knowledge sharing in a social network is not limited among individuals (Gong Y., Kim Y., Lee, D.R. 2013). One actor can share knowledge to a group of people, and /or accept knowledge from a group of people. Furthermore, personal requirement of knowledge is not necessarily a two-way exchange. That one actor needs knowledge from another actor does not mean there is Symmetric demand. Another possible reason is that trust is usually produced following reciprocity, so reciprocity influences the quality of knowledge sharing indirectly by means of trust, rather than directly (Turel, O.,Serenko, A. 2012).

5 Conclusion

This paper analyzed how social capital to affect knowledge sharing in three dimensions in a social network. We formulated conceptual model and put forward research hypothesis on a theoretical analysis. Capture tools are used to collect the user data on Zhihu and a research based on questionnaire is carried out to acquire the centrality and basic data, then multiple regression analysis are conducted to test the hypothesis. The main conclusions are as follows:

Firstly, social network centrality has significant positive influence on the quality of knowledge sharing, which can lead to a conclusion that stimulating users with high centrality to share knowledge can produce more high-quality knowledge. The social networking site can employ algorithm technology or working staff to establish criteria to identify the users in the central position, also can organize regular meetings or parties to familiarize members and recommend charismatic users with high reputation high centrality, aiming to strengthen the recognition and belonging to a social networking users and the sense of trust to other users.

Secondly, common language and shared vision, the two dimensions of cognitive capital, of have significant positive influence on both quantity and quality of knowledge sharing, so enhancing common language and shared vision will help to promote the effect of knowledge sharing. For example, managers can classify and label the users, calculate the correlation of the labels according to the algorithm, then recommend relevant groups and related problems on the basis of the calculating results to the user.

Thirdly, trust has significant positive influence on the quality of knowledge sharing in a social network. Guarantee mechanism should be established to improve and maintain the trust among users achieve higher quality of knowledge sharing. The users may be asked to provide their identities, such as names, identity certificates, certificate of academic degree or photos, etc., when registering, aiming to effectively reduce cheating risk in the network. On the premise of privacy security, a credit scoring system is recommendable to suggest high-quality users worthy of trust and communication.

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