



Effectiveness of Key Knowledge Spreader Identification in Online Communities of Practice: A Simulation Study from Network Perspective

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ABSTRACT

With the rapid development of online communities of practice (CoPs), how to identify key knowledge spreader (KKS) in online CoPs has grown up to be a hot issue. In this paper, we construct a network with variable clustering based on Holme-Kim model to represent CoPs, a simple dynamics of knowledge sharing is considered. Kendall's Tau coefficient is used to investigate the effectiveness of four typical KKS indicators from a network perspective. We also examine the relationship between knowledge acceptance rate (KAR) of members in CoPs and the effectiveness of indicators. The results conclude that variable clustering will lead to unstable fluctuation of the effectiveness of KKS indicators, and the change of KAR during knowledge sharing will lead to effectiveness of KKS indicators fluctuating with a U-shape. The conclusion suggests that indicators should be used under suitable conditions in practice to improve the efficiency of knowledge sharing.

Keywords: communities of practice (CoPs), knowledge sharing, key knowledge spreader (KKS), Holme-Kim model, knowledge acceptance rate (KAR), network

INTRODUCTION

In recent years, communities of practice have been growing rapidly and becoming the focus of research (Ardichvili, Page, & Wentling, 2003; Eckert, 2006). Community of practice (CoP) was firstly introduced by Lave and Wenger (1991) who defined it as “an activity system about which participants share understandings concerning what they are doing and what that means in their lives and for their community”. CoPs are regarded as a platform for sharing and spreading knowledge, a key vehicle of learning and education (Wenger, McDermott, & Snyder, 2002; Schenkel & Teigland, 2008; Kirschner & Lai, 2007).

The early research on CoPs was focusing on face-to-face and collocated communities (Lave & Wenger, 1991; Wenger, 1998). But with the immense development of internet technology, online communities of practice (online CoPs) have emerged and increased significantly. The key challenge of online CoPs is the spreading of knowledge, namely the willingness to share knowledge with other CoP members. Knowledge sharing refers to the

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State of the literature

- Current studies focus on knowledge sharing which is critical in online communities of practice from different theories and perspectives.
- Key knowledge spreader identification in online CoPs has become a hot issue. A lot of studies are offered but often fail to produce desired results in practice due to rapid evolution of online CoPs.
- How to deal with the dynamic evolution of online CoPs and identify key knowledge spreader to boost the efficiency of knowledge sharing has an important practical significance but relative studies are rare.

Contribution of this paper to the literature

- The study examines the effectiveness of four typical key knowledge spreader indicators in online CoPs from a network perspective.
- The results show variable clustering leads to unstable fluctuation of the effectiveness of key knowledge spreader indicators.
- The study indicates improving the efficiency of knowledge sharing in online CoPs can only be achieved by selecting appropriate indicators under various scenarios.

provision of task information and know-how to help others and to collaborate with others to solve problems, develop new ideas, or implement policies or procedures (Cummings, 2004; Wang & Noe, 2010). In a typical online CoP (i.e. LinkedIn), people would join in the community from all over the world and have social interaction, participation and engagement with others which results in knowledge sharing through the CoP. Many scholars argue that knowledge sharing is critical in fostering virtual communities from different theories and perspectives. For example social cognitive theory and social capital theory (Chiu, Hsu, & Wang, 2006), interpersonal relationship perspective (Ma & Yuen, 2010), empirical studies (Yu, Lu, & Liu, 2010; Lin & Huang, 2013) and computational approaches (Soller, 2004; Wang, Gwebu, & Shanker, 2009).

The intricate and complex relationship between CoP members makes network theory applicable in the study of knowledge sharing in online CoPs. Cowana and Jonardb (2004) use network model to examine the relationship between network architecture and knowledge sharing (diffusion) performance. They conclude that the dynamics of knowledge transmission is affected by the architecture of connections among agents. Following James and Gao (2004), a virtual knowledge sharing community that is based on decentralized P2P technology is proposed. And four application features are introduced to have capability of motivating the members of community to share knowledge with each other. Fritsch and Monz (2010) analyze knowledge sharing in a sample of 16 German regional innovation networks and indicate that strong ties are more beneficial for the exchange of knowledge than weak ties. Stewart and Abidi (2012) investigate knowledge sharing dynamics of a community of practice through an online discussion forum. They evaluate the communication patterns of the community members using statistical and social network analysis methods to better understand how the

online community engages to share experiential knowledge. The results reveal that the discussion forum is dominated by a single institution and a single profession.

From a network perspective, how to identify key knowledge spreader (KKS) in online CoPs has become a hot issue in knowledge management and education areas. However, various empirical studies have found that indicators derived from static network often fail to produce the desired results in practice. The possible reason is the rapid evolution of network topology. The structural characteristics of online CoPs, especially clustering coefficient, have changed greatly, resulting in malfunction of these indicators. Therefore, how to deal with the dynamic evolution of online CoPs, and then identify KKS which could boost the efficiency of knowledge sharing has an important practical significance.

In order to study the effectiveness of KKS identification in online CoPs with dynamic structures, in this paper a network model based on the Holme-Kim model is established, the knowledge sharing capacity of each member of online CoPs is computed through the dynamics of knowledge sharing. The Kendall's Tau coefficient is used to measure the consistency between KKS indicator sequence and knowledge sharing capacity sequence, the trends of the effectiveness of KKS indicators with the change of knowledge acceptance rate are also analyzed. In the following section (section 2), we introduce a conceptual model of CoPs and dynamics of knowledge sharing used in the analysis. The simulations and results are presented in section 3. Section 4 gives the discussion, conclusion and suggestions.

A CONCEPTUAL MODEL OF CoPs FROM NETWORK PERSPECTIVE

A conceptual network model is used to represent CoPs. The clustering coefficient of a CoP is the probability that any two members who have knowledge sharing behaviors with member i also have knowledge sharing behaviors with each other. In the network theory, clustering coefficient can be expressed as the ratio of number of triangles in a network that contains nodes i to the number of connected triples with node i centered. So suppose the adjacency matrix of the network is

$$A = (a_{ij})_{N \times N} \tag{1}$$

The number of triangles containing i is:

$$E_i = \sum_{k>j} a_{ij} a_{jk} a_{ki} \tag{2}$$

The clustering coefficient can be computed as:

$$C_i = \frac{\sum_{j \neq i, k \neq j, k \neq i} a_{ij} a_{ik} a_{jk}}{\sum_{j \neq i, k \neq j, k \neq i} a_{ij} a_{ik}} \tag{3}$$

So the clustering coefficient C is computed as follow:

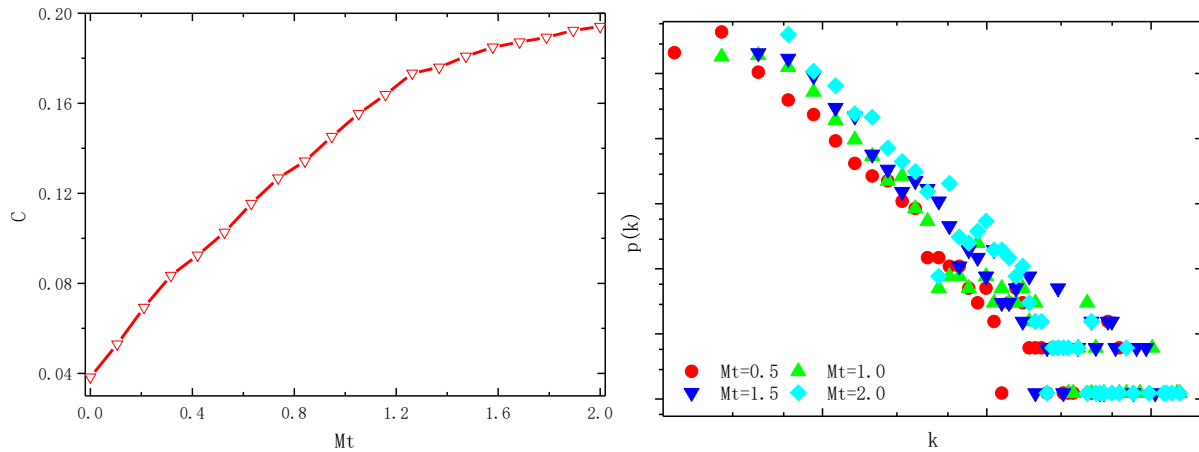


Figure 1. Variable clustering and scale-free characteristics of online CoPs

$$C = \frac{1}{N} \sum_{i=1}^N \frac{\sum_{j \neq i, k \neq j, k \neq i} a_{ij} a_{ik} a_{jk}}{\sum_{j \neq i, k \neq j, k \neq i} a_{ij} a_{ik}} \tag{4}$$

With the knowledge sharing behaviors increase, the clustering coefficient of online CoPs will perform an increase. In order to incorporate this character, it is necessary to establish a network model with variable clustering coefficient. In this paper Holme-Kim model is used to establish the network (Holme & Kim, 2002).

Holme-Kim model has not only scale-free characteristics of BA scale-free network, but also a high clustering coefficient like small-world network. Holme and Kim first initialize the nodes and let the initial nodes form a ring. At each step, add a new node *i* with *m* edges. The new node *i* selects a node *j* randomly from the existing node set *V*, if the node *i* and the node *j* are successfully connected, then randomly select a node from the neighbors of the node *j*, and the edge of *i* and *r_j* is constructed with probability $P_i = M_i / (m - 1)$ to form a triangle where *M_i* can be seen as a variable parameter.

Select $m_0 = 4, m = 3, N = 10000, M_t \in [0, 2]$ and *M_t* will increase by 0.1. It can be seen that the clustering coefficient increases with the increment of *M_t*, which represents the average frequency of knowledge sharing behaviors of members in the online CoPs. Obviously the network is also a scale-free network (see Figure 1).

In order to calculate knowledge sharing capacities of members in CoPs, we propose a simple dynamics of knowledge sharing: Suppose there only exist two states of members, knowledge spreaders and knowledge learners. Knowledge spreader *i* will share knowledge to its neighbors, the neighbors will accept the knowledge by the probability KAR which is knowledge acceptance rate. If *i*'s neighbor *j* can accept the knowledge, *j* will switch its state

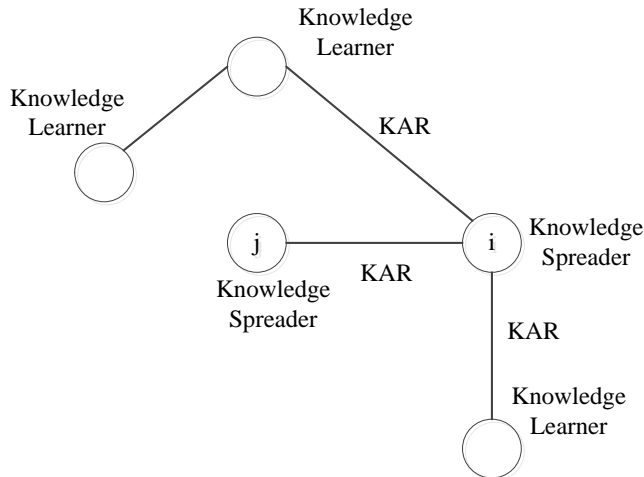


Figure 2. The dynamics of knowledge sharing: *j* will switch its state due to knowledge sharing from *i* from knowledge learner to knowledge spreader. Then *j* will also spread the knowledge to its neighbors (as referred **Figure 2**).

The knowledge sharing capacity of *i* can be computed by the ratio of knowledge spreaders in all the members in the CoPs until no more members can switch their states.

The simulation is carried out to obtain the sequence of knowledge sharing capacities: $\{K_1, K_2, \dots, K_N\}$.

In this paper, we select four types of KKS indicators: degree centrality, betweenness centrality, closeness centrality and eigenvector centrality. The sequence of degree centrality of the members in the online CoPs can be expressed as $\{k_1, k_2, \dots, k_N\}$. The closeness centrality sequence is $\{cc_1, cc_2, \dots, cc_N\}$ where $cc_i = \frac{N}{\sum_{j=1}^N d_{ij}}$ and d_{ij} is the distance from node *i* to node *j*. The

eigenvector centrality sequence can be expressed as $\{ec_1, ec_2, \dots, ec_N\}$ where $ec_i = c \sum_{j=1}^N a_{ij} x_j$.

The sequence of betweenness centrality can be expressed as $\{bc_1, bc_2, \dots, bc_N\}$, where g_{st} is the number of shortest paths from node *s* to node *t*, n_{st}^i is the number of shortest path through node *i* among g_{st} .

SIMULATIONS AND RESULTS

Kendall's Tau coefficient can be used to measure the correlation of two random variables, which is calculated as follows:

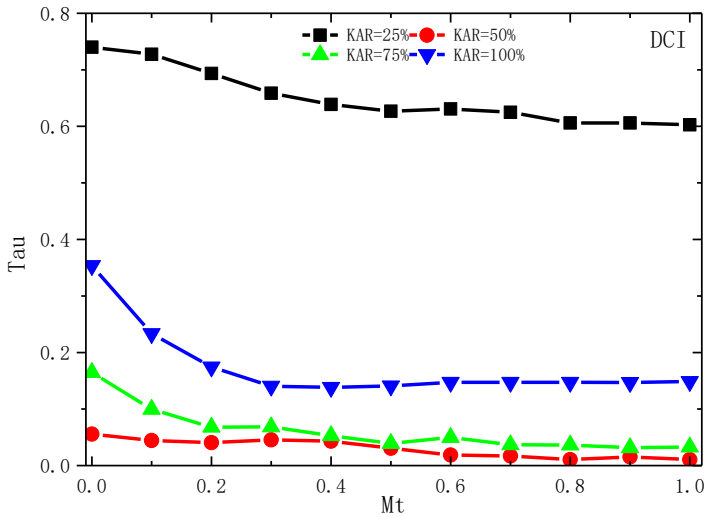


Figure 3. Degree Centrality Indicator with variable clustering coefficient

$$\tau = \frac{\sum_{i=1}^N \sum_{j=1}^N \text{sgn}[(x_i - x_j)(y_i - y_j)]}{N(N-1)} \tag{5}$$

The range of τ is between -1 and 1. When $\tau = 1$, it means that the two random variables have the same correlation; when $\tau = -1$, the two random variables have the opposite correlation; when $\tau = 0$, the two random variables are independent of each other (Centola, 2010). In this paper, the Kendall's Tau coefficient is used to measure the consistency of knowledge spreading capacity sequence and KKS indicator sequence. By calculating the Kendall's Tau coefficient, we can calculate the effectiveness of KKS indicators.

Using degree centrality as a KKS indicator, as in **Figure 3**, it can be observed that with variable clustering coefficient, the effectiveness of degree centrality indicator (DCI) shows a certain degree of fluctuation. The effectiveness of DCI decreases with the increase of clustering coefficient, and parameter KAR in the process of knowledge sharing has an impact on the effectiveness. When KAR is 25%, the effectiveness is at a high level with a steady decrease from 0.75 to 0.6. When KAR is 100%, the effectiveness of DCI decreases from near 0.4 to 0.15, and when KAR is 75% and 50%, the effectiveness of DCI reduces from 0.16 and 0.05 to 0.03 and 0.01 respectively.

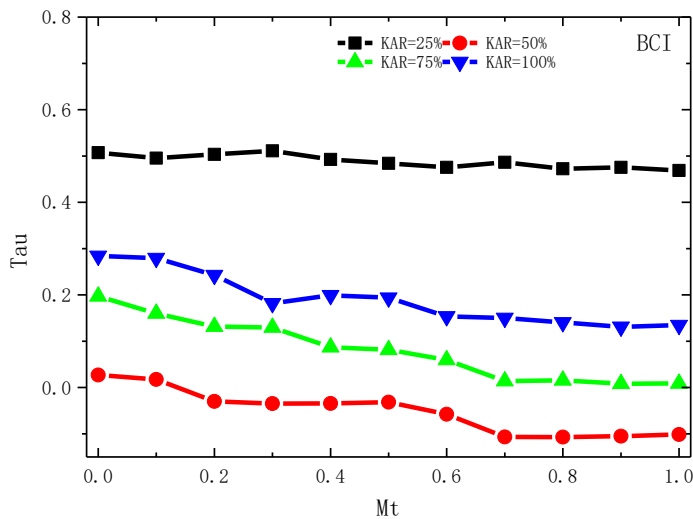


Figure 4. Betweenness Centrality Indicator with variable clustering coefficient

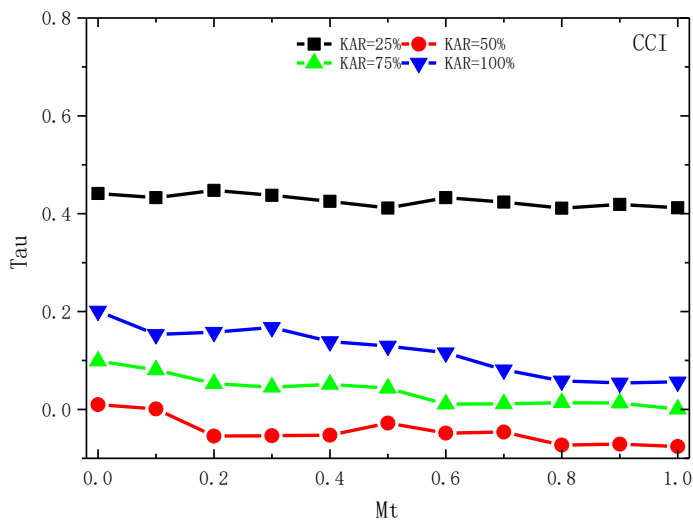


Figure 5. Closeness Centrality Indicator with variable clustering coefficient

Effectiveness of Betweenness Centrality Indicator (BCI) is different under different clustering coefficients. It can be seen from Figure 4 that the effectiveness decreases with the increase of the clustering coefficient, and KAR has an influence on the change of the effectiveness. When KAR is 25%, the effectiveness is at 0.5 steadily. When KAR is 100%, the effectiveness of BCI is reduced from near 0.3 to 0.13, and when KAR is 75%, its effectiveness decreases from 0.19 to close to 0. It is worth noting that when KAR is 50%, the Kendall's Tau coefficient decreases to a negative value with the increase of clustering coefficient which indicates that BCI at this time has a poor effect of identification.

Variable clustering coefficient leads to fluctuation of effectiveness of the Closeness Centrality Indicator (CCI). It can be seen from Figure 5 that the effectiveness of CCI reduces with the increase of clustering coefficient, and the effect of KAR on the effectiveness is obvious.

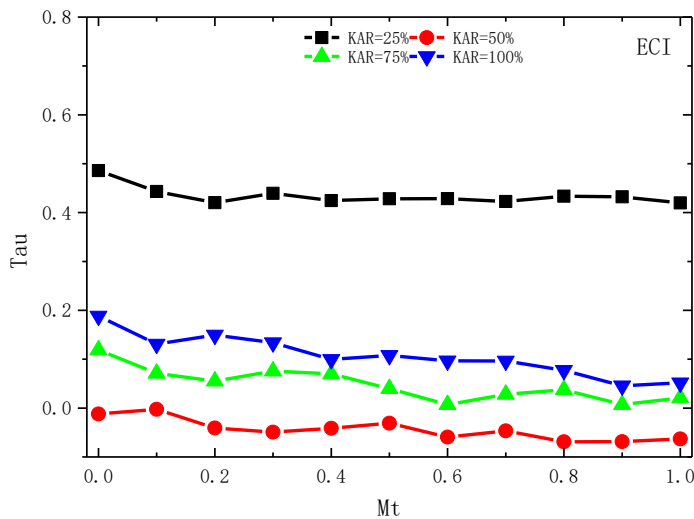


Figure 6. Eigenvector Centrality Indicator with variable clustering coefficient

When KAR is 25%, the effectiveness is at around 0.42. When KAR is 100%, the effectiveness of CCI is reduced from 0.2 to 0.1, and when KAR is 75%, the effectiveness of CCI decreases from 0.1 to close to 0. Similar to Betweenness Centrality Indicator, when KAR is 50%, the Kendall's Tau coefficient decreases to a negative value with the increase of the clustering coefficient indicating that CCI at this time becomes less effective.

Effectiveness of Eigenvector Centrality Indicator (ECI) can be seen in **Figure 6**. The effectiveness of ECI decreases with the increase of clustering coefficient, and the fluctuation trend of effectiveness is different under different values of KAR. When KAR is 25%, the effectiveness is at 0.43 steadily. When KAR is 100%, the effectiveness of ECI is reduced from 0.2 to 0.05, and when KAR is 75%, the effectiveness of ECI decreases from 0.1 to close to 0. When KAR is 50%, the Kendall's Tau coefficient decreases to a negative value with the increase of the clustering coefficient. It is indicating that ECI is less effective at that time.

From the above, it is found that the effectiveness of each indicator is negative when KAR is about 50%, which is significantly different from that of KAR at 25%, 75% and 100%. Therefore, the effectiveness of each indicator is further observed with KAR as a variable. As shown in **Figure 7**, the effectiveness of DCI has the same trend with KAR increases under different M_t . Specifically, when KAR is in the range of 10% to 25%, the effectiveness of DCI is stabilized in the range of 0.6 to 0.8, and when KAR is in the range of 25% to 60%, the effectiveness of DCI gradually decreases, even when KAR equals to 60% the effectiveness becomes negative. But with KAR continues to increase, there has been a rebound and the effectiveness of DCI finally becomes positive.

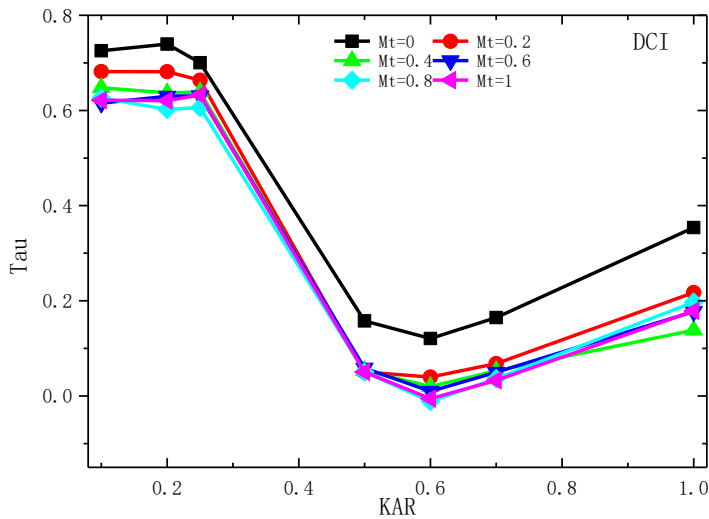


Figure 7. Degree Centrality Indicator with variable KAR

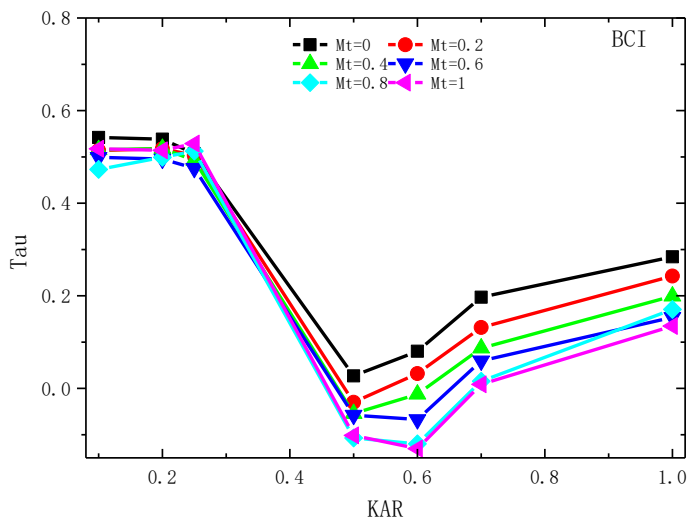


Figure 8. Betweenness Centrality Indicator with variable KAR

As shown in **Figure 8**, with KAR increasing, the effectiveness of BCI has the same trend under variable M_t . But the change of KAR will lead to U-shape of effectiveness, when KAR is in the range of 10% to 25%, the effectiveness of BCI is stabilized at about 0.5, and when KAR is 25% to 60%, the effectiveness of BCI decreases, and even when KAR is 60% the effectiveness becomes also negative. But with KAR continues to increase, the effectiveness finally turns to be positive as DCI.

Just as BCI, we can see from **Figure 9** that effectiveness of CCI also has the U-shape trend when KAR increases. In particular, the effectiveness goes to negative when KAR in the range of 50% to 60%. And finally the effectiveness goes up but still a little lower than BCI.

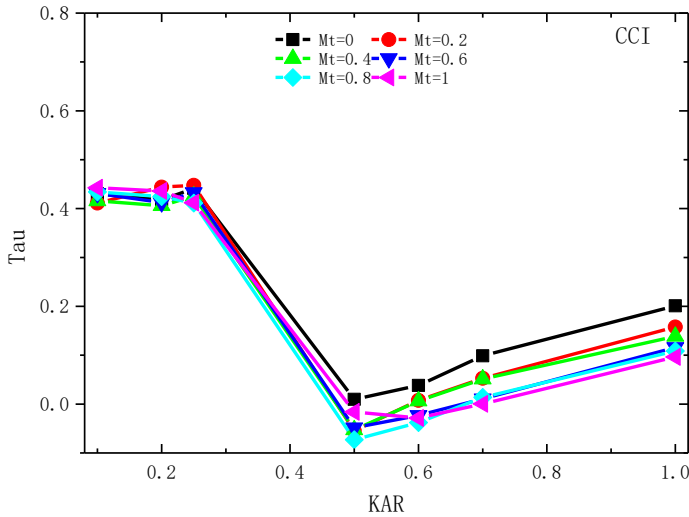


Figure 9. Closeness Centrality Indicator with variable KAR

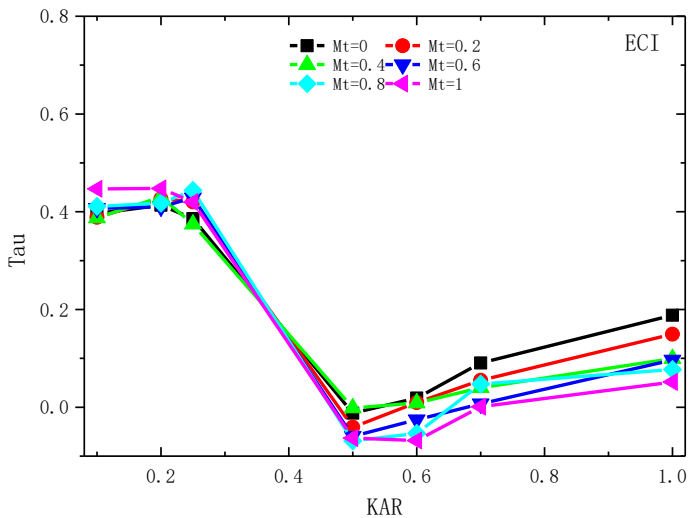


Figure 10. Eigenvector Centrality Indicator with variable KAR

For ECI, The effectiveness is the worst. The effectiveness sharply declines to negative during KAR increasing from 50% to 60%. When KAR increase from 60% to 100%, the effectiveness slightly rises up but still at a very low level (see [Figure 10](#)).

DISCUSSION, CONCLUSION AND SUGGESTIONS

Previous studies have shown that the dynamics of knowledge sharing is affected by the architecture of online CoPs. A lot of studies are offered but often fail to produce desired results in practice due to rapid evolution of online CoPs. Hence how to deal with the dynamic evolution of online CoPs and identify key knowledge spreader to boost the efficiency of knowledge sharing has an important practical significance, but relative studies are rare. From a network perspective, we explore the effectiveness of four typical key knowledge spreader

indicators in online CoPs. The results indicate that indicators should be used under suitable conditions because they will perform depending on some parameters like clustering and knowledge acceptance rate of CoP members. Our findings are consistent with the study conducted by Centola (2010) but in different areas. We believe the aim to improve the efficiency of knowledge sharing can only be achieved by selecting appropriate indicators under various scenarios prudently.

In this paper, we model knowledge sharing in online CoPs from a network perspective with variable clustering coefficient. Kendall's Tau coefficient is used to measure the effectiveness of four typical KKS indicators. We find that the effectiveness of KKS indicators are decreasing with the increase of the clustering coefficient while different indicators have different degrees of decline. In summary, Degree Centrality Indicator has the highest effectiveness and stability with variable clustering coefficient. And the second is Betweenness Centrality Indicator and Closeness Centrality Indicator. Eigenvector Centrality Indicator are not effective, and the stability of its effectiveness is also poor. Further adjust knowledge acceptance rate (KAR) of members and find that with the KAR increases, the effectiveness of KKS indicators are not linear but fluctuate with a U-shape. When KAR is small, the four indicators all perform well, but with KAR increases, the effectiveness of each indicator has a sharp decline. When KAR goes to the range of 50% to 60% the effectiveness is even negative, but with the KAR gets close to 100%, the effectiveness of all indicators gradually rise up and become positive at a certain range.

The model could be extended in several obvious ways. We have taken knowledge acceptance rate of members in CoPs as homogeneous. But this parameter is different depending on the personality of individual. Thus more refined dynamics of knowledge sharing should be considered. And the dynamic evolution of community structure may include other attributes such as path length, clique size and so on. Hence, more indicators and attributes should be included for future study. In addition, Holme-Kim model is based on undirected network, how to analyze the effectiveness of key knowledge spreader indicator on the directed network will be a topic further studied.

REFERENCES

- Ardichvili, A., Page, V., & Wentling, T. (2003). Motivation and barriers to participation in virtual knowledge sharing teams. *Journal of Knowledge Management*, 7(1), 64-77. doi:10.1108/13673270310463626
- Centola, D. (2010). The spread of behavior in an online social network experiment. *Science*, 329(5996), 1194-1197. doi:10.1126/science.1185231.
- Chiu, C. M., Hsu, M. H., & Wang, E. T. (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. *Decision support systems*, 42(3), 1872-1888. doi:10.1016/j.dss.2006.04.001
- Cowan, R., & Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of economic Dynamics and Control*, 28(8), 1557-1575. doi:10.1016/j.jedc.2003.04.002

- Cummings, J. N. (2004). Work groups, structural diversity, and knowledge sharing in a global organization. *Management science*, 50(3), 352-364. doi:10.1287/mnsc.1030.0134
- Eckert, P. (2006). Communities of practice. *Encyclopedia of language and linguistics*, 2(2006), 683-685. doi:10.1016/b0-08-044854-2/01276-1
- Fritsch, M., & Kauffeld-Monz, M. (2010). The impact of network structure on knowledge transfer: an application of social network analysis in the context of regional innovation networks. *The Annals of Regional Science*, 44(1), 21-38. doi:10.1007/s00168-008-0245-8
- Holme, P., & Kim, B. J. (2002). Growing scale-free networks with tunable clustering. *Physical review E*, 65(2), 026107. doi:10.1103/PhysRevE.65.026107
- Kirschner, P. A., & Lai, K. W. (2007). Online communities of practice in education. *Technology, Pedagogy and Education*, 16(2), 127-131. doi:10.1080/14759390701406737
- Kwok, J. S., & Gao, S. (2004). Knowledge sharing community in P2P network: a study of motivational perspective. *Journal of knowledge Management*, 8(1), 94-102. doi:10.1108/13673270410523934
- Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. New York: Cambridge University Press. doi:10.1017/cbo9780511815355.003
- Lin, F. R., & Huang, H. Y. (2013). Why people share knowledge in virtual communities? The use of Yahoo! Kimo Knowledge+ as an example. *Internet Research*, 23(2), 133-159. doi:10.1108/10662241311313295
- Ma, W. W., & Yuen, A. H. (2011). Understanding online knowledge sharing: An interpersonal relationship perspective. *Computers & Education*, 56(1), 210-219. doi:10.1016/j.compedu.2010.08.004
- Schenkel, A., & Teigland, R. (2008). Improved organizational performance through communities of practice. *Journal of knowledge management*, 12(1), 106-118. doi:10.1108/13673270810852421
- Soller, A. (2004). Computational modeling and analysis of knowledge sharing in collaborative distance learning. *User Modeling and User-Adapted Interaction*, 14(4), 351-381. doi:10.1023/B:USER.0000043436.49168.3b
- Stewart, S. A., & Abidi, S. S. R. (2012). Applying social network analysis to understand the knowledge sharing behaviour of practitioners in a clinical online discussion forum. *Journal of medical Internet research*, 14(6), e170. doi:10.2196/jmir.1982
- Wang, J., Gwebu, K., Shanker, M., & Troutt, M. D. (2009). An application of agent-based simulation to knowledge sharing. *Decision Support Systems*, 46(2), 532-541. doi:10.1016/j.dss.2008.09.006
- Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, 20(2), 115-131. doi:10.1016/j.hrmr.2009.10.001
- Wenger, E. (1998). *Communities of practice: Learning, meaning and identity*. Cambridge, UK: Cambridge University Press. doi:10.1017/cbo9780511803932
- Wenger, E., McDermott, R., & Snyder, W. (2002). *Cultivating communities of practice: A guide to managing knowledge*. Boston, MA: Harvard Business School Press. doi:10.1225/3308
- Yu, T. K., Lu, L. C., & Liu, T. F. (2010). Exploring factors that influence knowledge sharing behavior via weblogs. *Computers in Human Behavior*, 26(1), 32-41. doi:10.1016/j.chb.2009.08.0021

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