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# Understanding user behavioral patterns in open knowledge communities

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#### ABSTRACT

Open knowledge communities (OKCs) have become popular in the era of knowledge economy. This study aimed to explore how users collaboratively create and share knowledge in OKCs. In particular, this research identified the behavior distribution and behavioral patterns of users by conducting frequency distribution and lag sequential analyses. Some major problems, including the lack of certain significant behavioral sequences and the inadequacies of knowledge-sharing mechanisms and culture, were also determined. Moreover, this research discussed related problems and proposed several improvement measures for developing OKCs. Finally, the implications for researchers and practitioners were stated, and the shortcomings of this study were presented.

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#### **KEYWORDS**

Open knowledge community; sequential analysis; behavioral pattern; knowledge sharing

# Introduction

In the era of knowledge economy, knowledge has become a key driver for growth of regions and nations (Acs, Groot, & Nijkamp, 2002). Open knowledge communities (OKCs) have become popular in the past few years (Yang, Qiu, Yu, & Tahir, 2014). OKC is a virtual organizational form with specific interest in which knowledge collaboration can occur at an unparalleled scale and scope (Faraj, Jarvenpaa, & Majchrzak, 2011; Vries, Bloemen, & Roossink, 2000). OKCs can be used as knowledge management tools and virtual learning environments for learners (Zeng, 2011) and can emphasize the dynamic processes of transforming prevailing knowledge and practices (Paavola, Lipponen, & Hakkarainen, 2004).

OKCs have the following common features: (1) any valid user can form new knowledge entries and co-edit existing ones; (2) various interactions, such as comment, collect, score, vote, and share, can be realized between users and knowledge entries. Compared with the traditional knowledge repository, OKCs have inherent advantages in attracting user participation, encouraging collaboration, and promoting knowledge sharing (Yang et al., 2014).

Many researchers have devoted significantly more attention to OKCs and explored the process, mechanism, and influencing factors of knowledge creation and sharing (Chang & Chuang, 2011; Looi & Chen, 2010; Paavola et al., 2004; Tseng & Kuo, 2014). Nonetheless, the behavioral patterns and rules of users in OKCs are yet to be thoroughly identified and should be explored further. Previous research on user behavior in OKCs mainly investigated specific behaviors, including vandalism (Shachaf & Hara, 2010), sharing (Yi, 2009), and collaboration behaviors (Faraj et al., 2011) while neglecting the exploration of behavioral sequences. In recent years, with the development of

CONTACT Xianmin Yang yangxianmin8888@163.com Research Center of Smart Education, Jiangsu Normal University, No. 101, Shanghai Road, Tongshan District, Xuzhou, Jiangsu Province, People's Republic of China 2017 Informa UK Limited, trading as Taylor & Francis Group learning analytics, scholars from e-learning areas began to study online learning behavioral sequences. Hou, Sung, and Chang (2009, 2011) explored teachers and students' behavioral patterns in the contexts of online asynchronous discussion. Hwang and Chen (2016) investigated the students' behavioral sequences in an inquiry-based ubiquitous gaming. In addition, there are some studies focused on learners' online collaborative translation behavior (Yang et al., 2014), informal learning behavior through mobile devices (Sung, Hou, Liu, & Chang, 2010) and knowledge construction behavior during online collaborative learning (Zhang, Liu, Chen, Wang, & Huang, 2017). However, at present, the studies on behavioral sequences in OKC are rare.

The present study aims to investigate the behavioral patterns of users in OKCs, identify potential problems, and propose several improvement measures. By analyzing the user behaviors that occur in OKCs, we can better comprehend the habitual behavior of users, discover potential problems, optimize the related community functions and mechanisms, and ultimately promote the creation and sharing of more high-quality knowledge under mass collaboration in OKCs. To this end, three research questions are specified as follows:

- (1) How are user behaviors distributed in OKCs?
- (2) What behavioral sequences exist in the process of creating and sharing knowledge in OKCs?
- (3) What problems can be identified by analyzing the user behaviors in OKCs?

## Method

In this study, lag sequential analysis (LSA) (Bakeman & Gottman, 1997) was used to probe the user behavioral patterns. Sackett (1978) developed LSA to estimate the probability of occurrence for any behavior of a repertoire against time. It is mainly used to examine whether certain human behaviors followed by another behavior occur with statistical significance (Hawks, 1987). Frequency distribution analysis was performed to investigate the frequencies of different operant behaviors.

#### **Research object**

Currently, the biggest OKC in the world is the online encyclopedia Wikipedia (http://www.wikipedia. org), which is a vast, constantly evolving tapestry of interlinked articles (Milne & Witten, 2013). In fact, besides Wikipedia, there are also some other OKCs running online in China, such as the Learning Cell Knowledge Community (LCKC) (http://lcell.bnu.edu.cn), Baidu Baike (http://baike.baidu.com), Hudong Baike (http://www.baike.com/), etc. The above-mentioned OKCs have gained popularity by more and more Chinese internet users.

In order to investigate user behavior patterns in OKCs, we have to get all the related behavior logs. However, most communities, such as Wikipedia, Baidu Baike, and Hudong Baike, do not provide public data of user behavior. Adopting the convenience sampling strategy, LCKC, developed by Beijing Normal University, was selected as the object of study. One screenshot of LCKC was presented in Figure 1.

LCKC (http://lcell.bnu.edu.cn) is the bronze winner of Learning Impact 2014 and characterized by collaborative content editing, multiple interactions, and personal knowledge management (Yu, Yang, Cheng, & Wang, 2015). The main target users of LCKC are primary and secondary school teachers. As of September 2014, more than 3000 teachers from 300 primary and secondary schools in China use LCKC to co-author teaching plans and share teaching materials. Moreover, all user behavioral logs are automatically stored into the backend database of LCKC.

# Sampling

Behavioral logs between 1 September 2013 and 4 September 2014 were selected by operating the database of LCKC as the initial sample for this study. Logs that were unrelated to knowledge creation

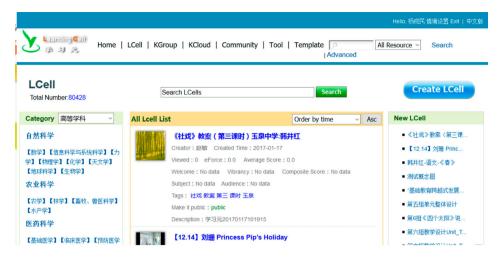


Figure 1. Screenshot of LCKC.

and sharing, such as log in, log out, register, search, and so on, were filtered out through executing SQL statements. Finally, 45,076 effective logs attached in 5,438 knowledge entries were selected as the final sample.

#### **Behavior coding**

In LCKC, any knowledge entry may experience three phases (Yang, 2015). The first phase is the appearing stage, in which a new knowledge entry with no content is formed by a user. This entry then enters the evolutionary stage, during which the creator and other collaborators begin to collaboratively input and edit contents. Within the knowledge entry, the users perform various interactions (comment, discuss, annotate, score, vote, share, upload, etc.) to promote the evolution of the entry. After a period of evolution, the knowledge entry moves into the mature stage, in which it becomes a relatively well-developed knowledge unit. In the third stage, users can also communicate and share information around the knowledge entry.

This research investigated the behaviors directly related to knowledge creation and sharing. Twelve user behaviors generated in Stages 2 and 3 were finally selected. A coding scheme was formulated to conduct the sequential analysis of user behaviors (see Table 1). In LCKC, all user behavior logs are recorded in the backend database of LCKC. Each record has several attributes, including behavior occurrence time, user identity, behavioral type, behavior description, and knowledge

Code	Behavior	Explanation				
EC	Edit content	Users edit content of the knowledge entry				
ED	Edit metadata	Users edit and improve the metadata of the knowledge entry, such as title, tags, classification, etc.				
IC	Invite collaborator	The creator invites other users to be the collaborators of the knowledge entry				
SC	Score	Users grade the knowledge entry according to his or her overall evaluation				
СМ	Comment	Users give comments to the knowledge entry				
PS	Post	Users carry out discussion in the forum				
AN	Annotate	Users record notes or propose suggestions on certain specific sections of the knowledge entry				
VT	Vote	Users vote for the reliability of the knowledge entry				
CL	Collect	Users add current knowledge entry to his or her favorites				
SH	Share	Users share the knowledge entry with others through recommending it to other communities				
UL	Upload material	Users upload related reference materials for extending learning				
DL	Download material	Users download the reference materials				

Table 1. Coding scheme for user behaviors in OKCs.

entry identity. In this study, all behavioral categories were automatically identified through checking the attribute of behavioral type in each behavior log record.

# Result

# Distribution of user behaviors

Table 2 displays the percentages of different operant behaviors in LCKC. This research identified that most frequently occurring behaviors are EC (edit content) and CM (comment). Such a finding indicates that when the users enter the page of one knowledge entry, they are particularly prone to edit the resource content or to input a comment. In most OKCs, EC and CM are usually the basic functions for supporting collaborative knowledge creation. This research discovered that among all behaviors, UL (upload material), IC (invite collaborator), and VT (vote) are the least occurring ones.

Credibility voting is one of the effective methods of solving the crisis of confidence (Yang et al., 2014) in OKCs. The LCKC allows users to vote on the credibility of a particular resource from five dimensions, namely, accuracy, objectivity, integrity, standardability, and update. In each dimension, the users can rate the credibility of a resource by using a five-point scale (from "very good" to "very poor"). Although the above evaluation index seems systematic, its actual application is very poor. Users scarcely spend time on voting primarily because of the overly complex design of the system, which requires long-time analysis and judgment of users. In this event, excessive cognitive load and psychological burden block user participation (Vonderwell & Zachariah, 2005). Accordingly, the voting mechanism in LCKC should be redesigned by simplifying the evaluation indicators and voting procedures.

Formal collaborator is a key role for promoting knowledge evolution. In contrast with the common user, collaborators have the right to check content editing and manage knowledge entries together with the creator. Table 2 indicates that, the scope and number of collaborators are limited for each knowledge entry. Lih (2004) identified that a positive correlation exists between the number of collaborators and the score of resources. Hence, to enhance resource quality, users should be encouraged to establish proper cooperation relationships in OKCs by means of recommending potential collaborators with professional background to resource creators and forming small interest circles automatically.

Uploading materials is an important knowledge-sharing behavior that enhances the understanding of learners. The main reasons users seldom upload and share learning materials may be as follows: (1) users lack the motivation and awareness in sharing materials; (2) the community culture of knowledge sharing has not been established; (3) the usability of upload function is not satisfactory; more operational procedures are required when uploading more than one item. In the future, OKCs should emphasize the creation of a community sharing mechanism and culture, and the optimization of efficiency of the upload function.

Behavior	Frequency	Percentage
Edit content	9692	21.50
Edit metadata	2361	5.24
Invite collaborator	1094	2.43
Score	4813	10.68
Comment	9486	21.04
Post	1586	3.52
Annotate	2488	5.52
Vote	964	2.14
Collect	2317	5.14
Share	5574	12.36
Upload material	1125	2.50
Download material	3581	7.94

 Table 2. Percentages of different behaviors.

#### Analysis of user behavioral sequential patterns

Each knowledge entry was treated as a unit, and all user behaviors attached to each knowledge entry were coded based on their temporal order. At present, several studies (Lai & Hwang, 2015; Wu, Chen, & Hou, 2016; Yang, Li, Guo, & Li, 2015) on online learning behavior employ the generalized sequential querier (GSEQ). In the present study, GSEQ 5.1 was adopted to conduct LAS.

The theory of LSA (Bakeman & Gottman, 1997) states that if the Z-value of a sequence in the adjusted residuals table (see Table 3) is greater than 1.96, then the connectivity of this sequence has attained statistical significance (p < .05). In this research, the behavior transition diagram was drawn to visually observe the significant behavioral sequences (see Figure 2). The node represents the behavioral category, the numerical value depicts the Z-value for the sequence, the arrowheads represent the transitional direction, and the thickness symbolizes the level of significance. Overall, the transition diagram can clearly be divided into three parts.

In part one, the user behaviors can be divided into five main kinds, namely EC, ED, IC, SH, and CL. Almost any of these behaviors connects with one another, which implies that a frequent mutual transition exists between them. This condition can be explained with the path  $EC \rightarrow ED \rightarrow IC \rightarrow EC$ . This path reveals that when the users completed content editing, they improved the basic information of knowledge entry. These users then invited others to become collaborators. After such an invitation, the users continued to improve the resource contents. In fact, some other closed-loop paths, such as  $EC \rightarrow ED \rightarrow SH \rightarrow CL \rightarrow IC \rightarrow EC$  can be observed. This instance suggests that when the users performed content and metadata editing, they might share this knowledge entry with others and add it to their favorites. After collection, these users invited collaborators and began to edit the contents again. The other significant transition paths include  $SH \rightarrow CL \rightarrow VT$ ,  $SH \rightarrow IC \rightarrow CL$ ,  $EC \rightarrow SH \rightarrow CL$ , and so on.

These sequences were extracted with the value of Z-score > 20, and the streamlined transition gram was obtained to identify the most significant behavioral sequences. Figure 3 illustrates four remarkable behavioral sequences, which are EC  $\rightarrow$  EC, EC  $\rightarrow$  ED  $\rightarrow$  SH, ED  $\rightarrow$  EC, SH  $\rightarrow$  SH, and CL  $\rightarrow$  CL. The behavior path EC  $\rightarrow$  EC shows that the users repeatedly edited the contents for a certain time, while EC  $\rightarrow$  ED  $\rightarrow$  SH has already been explained above. The path ED  $\rightarrow$  EC demonstrates that the users usually continued to edit the contents after modifying the resource metadata. SH  $\rightarrow$  SH shows that the users periodically shared their favorite resources with different users or social sites. Meanwhile, CL  $\rightarrow$  CL signifies that the users continuously collected multiple resources in a certain time period.

In part two, the user behaviors have four kinds, namely SC, CM, PS, and VT. The highly significant behavioral sequences (Z-score > 20) are SC  $\rightarrow$  CM, CM  $\rightarrow$  SC, CM  $\rightarrow$  CM, and PS  $\rightarrow$  PS. The behavior paths SC  $\rightarrow$  CM and CM  $\rightarrow$  SC indicate that the users usually inputted comments and score for the knowledge entry successively. The reason behind this occurrence is the fact that the functions of

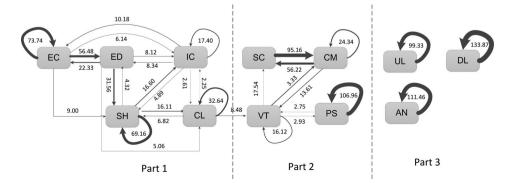


Figure 2. Behavioral transition diagram.

Table 3. Adjusted residuals table (Z-scores).

	,		,									
	EC	ED	IC	SC	CM	PS	AN	VT	CL	SH	UL	DL
EC	73.74*	56.48*	6.14*	-24.03	-41.29	-14.01	-8.28	-13.16	-8.03	9.00*	-2.19	-32.07
ED	22.33*	-6.32	8.12*	-10.82	-16.93	-8.72	-8.70	-5.27	5.06*	31.56*	1.02	-13.39
IC	10.18*	8.34*	17.40*	-8.52	-10.11	-2.38	-1.17	-2.78	2.61*	4.89*	1.22	-8.33
SC	-27.13	-15.51	-10.30	-7.51	95.16*	-10.98	-15.51	1.46	-10.33	-23.73	-10.04	-20.82
CM	-26.15	-19.72	-10.29	56.22*	24.34*	-4.95	-12.17	13.61*	0.10	-27.02	-12.01	-3.09
PS	-12.68	-8.58	-3.17	-6.09	-9.11	106.96*	-7.17	2.75*	-3.01	-13.21	-5.39	-3.79
AN	-1.89	-11.52	-2.71	-9.26	-15.89	-8.13	111.46*	-3.12	-7.59	-14.49	-5.08	-15.64
VT	-11.32	-6.82	-3.74	17.54*	3.33*	2.93*	-2.84	16.12*	1.63	-9.40	-3.93	-0.10
CL	-9.54	-4.62	2.25*	-2.70	-0.52	-1.26	-6.81	8.48*	32.64*	6.82*	-4.62	-9.60
SH	-6.34	4.32*	16.60*	-16.35	-20.15	-12.37	-10.28	-8.61	16.11*	69.16*	-3.18	-19.63
UL	-3.76	-3.23	0.96	-9.35	-12.96	-5.69	-3.62	-4.74	-4.54	-0.48	99.33*	-5.88
DL	-26.52	-14.40	-9.51	-0.41	-20.74	-3.27	-15.58	0.17	-11.67	-21.40	-8.22	133.87*

\*p < .05.

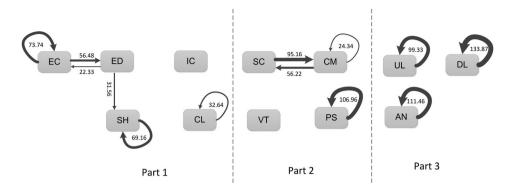


Figure 3. Behavioral transition diagram with Z-score > 20.

comment and score in most OKCs are always placed together, which is deemed helpful for increasing the rate of user scoring. Interaction is a required element of collaborative knowledge construction (Puntambekar, 2006). Comment and post are two of the most common means of interaction in OKCs. Meanwhile, the behavior paths  $CM \rightarrow CM$  and  $PS \rightarrow PS$  imply that the users communicated with one another in the areas of comment and discussion.

However, Figure 2 demonstrates that the path CM $\rightarrow$ EC was missing. This instance suggests that when the users finished their discussion for a period, they did not improve the resource content according to the suggestions and ideas generated during their interactions. Similarly, the path PS  $\rightarrow$  EC was missing. In particular, CM  $\rightarrow$  EC and PS  $\rightarrow$  EC are important for optimizing resource content on time. Therefore, some behavioral guidance strategies, such as pop-up messages that remind users to improve resource content, should be developed to strengthen the missing paths. The path SC $\rightarrow$ VT should also be encouraged. Substantial user participation in voting can help the system judge and identify excellent resources with high credibility (Yang et al., 2014).

Part 3 includes three kinds of user behaviors, namely AN, UL and DL. These user behaviors were determined to form three self-reinforcing cycles: AN  $\rightarrow$  AN, UL  $\rightarrow$  UL, and DL  $\rightarrow$  DL. These paths denote that the users tended to upload, download, or annotate a resource material repeatedly for a certain time. Annotate is another means of interacting among the users with a percentage of 5.52% in Table 2. Similar to the case of CM and PS, the path AN  $\rightarrow$  EC should also be reinforced. The lack of remarkable path DL  $\rightarrow$  UL indicates that the users preferred to enjoy than to contribute in online communities and, in most cases, lacked sufficient motivation to contribute. This finding conforms to the conclusion of Harper, Li, Chen, and Konstan (2007). Users shy away from contributing knowledge because of numerous reasons (Ardichvili, Page, & Wentling, 2003). Table 2 reveals that the percentage of DL (7.94%) is four times the number of UL (2.50%), which implies that the benign community culture of sharing has not been established in LCKC. The virtuous circle of UL  $\rightarrow$  DL  $\rightarrow$  UL is required to implement the sustainable knowledge sharing in OKCs. Accordingly, users should be encouraged to upload more related materials with high quality attached to the knowledge entries after downloading by constructing the incentive mechanism and sharing culture.

## Discussion

By analyzing the user behaviors in LCKC, this research generally observed two evident problems: (1) some significant behavioral sequences beneficial for knowledge evolution did not emerge, and (2) users did not contribute and share materials adequately; this undertaking is deemed harmful for constructing a healthy community culture of sharing.

#### Guiding user behaviors to promote knowledge evolution

Knowledge evolution signifies that a knowledge entry develops over time (Sun, 2011). The active participation of users lays the foundation for the rapid growth of OKCs. However, apart from the contribution of users, the proper guidance of their behaviors is also vital for promoting the orderly evolution of knowledge in OKCs. The results of the above behavioral sequential analysis indicated some problems. For instance, the lack of behavioral transition routes (e.g.  $CM \rightarrow EC$  and  $DL \rightarrow UL$ ) contradicted the quick evolution of knowledge and the formation of benign community knowledge-sharing culture.

Moreover, the existing routes of AN  $\rightarrow$  AN, CM  $\rightarrow$  CM, and PS  $\rightarrow$  PS showed that the users were continuously discussing in OKCs. Nevertheless, an obvious gossip problem (GP) was discovered through content analysis of some extracted comments. Such a discovery suggests that when somebody posted a content unrelated to the current discussion topic, the others would be attracted to become involved in the invalid interaction. GP was also discovered by other researchers in the unsupervised online discussion activity (Hou, Chang, & Sung, 2008). GP ensures that the interactions of users would deviate from the normal knowledge construction. Table 4 shows part of the continuous invalid discussions among users on the knowledge entry with number #22487.

Knowledge value is represented and sublimated in constant communications. The guidance mechanism of user behaviors should be provided in OKCs to facilitate the occurrence of more effective interaction behaviors. To resolve GP, some scholars (e.g. Aroyo & Kommers, 1999; Hou et al., 2009) proposed the integration of an intelligent agent in various discussions to automatically identify the gossip and intervene instantly. Input and output information are vital for successfully constructing knowledge (Du & Wagner, 2007). In this situation, promoting the integration of good suggestions and good ideas into resource contents should be considered in developing OKCs. This proposition implies that the measures for promoting the occurrence of transition routes such as  $CM \rightarrow EC$ , PS  $\rightarrow$  EC, and AN  $\rightarrow$  EC are required. In the process of user discussions, the system could intelligently identify and extract potentially novel ideas and finally pop up to remind users to improve resource contents according to the newly generated ideas and suggestions. In terms of intelligent extraction technology, different solutions (e.g. syntactic and lexical cues, learning-based anaphora resolution technique, etc.) have been proposed (Qiu, Liu, Bu, & Chen, 2011).

Table 2 illustrates that the behaviors of score and vote were relatively rare. Scoring and voting are rather useful for evaluating the quality of resources in OKCs. The functions of OKCs should be simplified as much as possible to reduce the cognitive load of users and to increase their participation in scoring and voting. Some large OKCs (e.g. Baidu Baike) have already replaced the five-star rating with significantly simpler means, such as vote up and down. The perceived ease of use influences the intention of users to adopt a certain technology or system (Davis, Bagozzi, & Warshaw, 1989).

#### Constructing the mechanism and culture of knowledge sharing

Table 2 indicates that the behavioral percentage of uploading materials was only 2.50%, whereas the downloading material percentage was four times the number of the former. The procedure of seeking a balance between the contribution and enjoyment of users and the strategies for prompting more users to be interested in sharing knowledge and wisdom in OKCs have become an important research issue (Ardichvili et al., 2003).

Table 4. Extraction of partial invalid discussion.

ID	Time	Author	Content	Operation
#22487	2013-6-23 23:04:27	HXY	I am coming. Welcome me boys and girls.	Comment
#22487	2013-6-23 23:05:41	YTY	Yeah! Applaud!	Comment
#22487	2013-6-23 23:06:18	PQQ	Fighting, my friends!	Comment
#22487	2013-6-23 23:06:26	YTY	Our group is the best. Thanks everybody!	Comment

Thus far, the issue of knowledge sharing in OKCs has been explored by several researchers (Wang, Noe, & Wang, 2014; Zhao, Liang, Liu, & Yu, 2013). The major influence factors consist of the willingness and attitude of knowledge sharing, self-efficacy of knowledge innovation, subjective norms, and social relationship (Zhang & Zhao, 2012). Wang et al. (2014) determined that evaluation and reward are positively related with knowledge sharing. To promote knowledge sharing in OKCs, we should take measures to (1) stimulate user knowledge-sharing motivation, (2) correct their attitudes toward knowledge sharing, (3) establish feasible community knowledge-sharing norms, and (4) formulate the incentive mechanism and strengthen social relationships among users for enhancing their sense of belongingness. Moreover, the sharing of external knowledge in other OKCs should also be taken seriously by aggregating external learning resources and interconnecting them among related communities (Zhao et al., 2013).

Culture influences human cognitive styles and techniques and online behaviors (Fiske & Taylor, 2007). Other than establishing related mechanisms, a reliable community culture of knowledge sharing should be developed to provide users with guidelines that can help them to gradually learn how to efficiently create and share knowledge. The following measures are proposed to construct a community knowledge-sharing culture: (1) community rules and regulations should be formed to protect the rights of users and their interests in knowledge creation and sharing; (2) a convenient knowledge-sharing environment with high reliability and security should be constructed, which would enable automatic identification of trusted users and the filtering out of inferior resources; (3) provide instant support for users in creating and sharing knowledge any time and any place with all kinds of mobile devices; (4) increase the ability of personalized knowledge recommendation (Liang, Yang, Chen, & Ku, 2008) and push related knowledge and people to different users based on their personalized interest models.

# Conclusion

In this study, we explored how users collaboratively create and share knowledge in OKCs. By combing methods of frequency distribution analysis and LSA, users' behavior distribution and behavioral patterns were identified. Among the major 12 kinds of behaviors, content edit and comment occurred most commonly, while uploading material, inviting collaborators, and credibility voting appeared with the minimum number of times. The fewer occurrences do not mean that they are not important for promoting knowledge creation and share. On the contrary, they should be strengthened by means of enhancing usability, intelligent recommendation, etc. With respect to behavioral patterns, we found several extremely significant behavioral sequences (i.e.  $EC \rightarrow ED \rightarrow SH$ ,  $EC \rightarrow EC$ ,  $SH \rightarrow SH$ ,  $SC \rightarrow CM$ ,  $UL \rightarrow UL$ ,  $DL \rightarrow DL$ ,  $PS \rightarrow PS$ ,  $AN \rightarrow AN$ ). These sequences are vital for promoting knowledge improve continually and user interactions in OKCs. However, we also found some major limitations representing by the lack of certain significant behavioral sequences and the inadequacies of knowledge-sharing mechanism and culture. Accordingly, we provided several improvement measures in the above.

The above findings will be helpful for improving current OKCs, particularly for the communities in the early stage of development. Implications implied by this study can be summarized as follows: (1) establish the guidance and feedback mechanisms to guide user behaviors towards knowledge evolution and in-depth interaction by using intelligent agent technology and text mining (e.g. opinion extraction); (2) pay more attention to construct community culture of knowledge sharing; (3) reference the design thought of SNS (Social Network Site, such as Facebook, Twitter, etc.) to enhance the system usability and the user viscosity. Additionally, researchers should conduct further studies on user behaviors to clarify the behavior mechanisms and rules in different kinds of OKCs.

Although the result of this study could help us further understand user behaviors and the limitations in OKCs, there were still some drawbacks in this study. We selected one knowledge community mainly serving primary and secondary school teachers. Different user groups may have distinct behavioral preferences and patterns. For example, the OKCs for enterprise employees might 254 🛛 🖌 X. YANG ET AL.

present unique significant behavioral sequences. Moreover, we just analyzed the frequencies and sequences of user behavior, neglecting the correlation between different behaviors.

In the future, we plan to select several different types of OKCs to investigate the distinctions in user behaviors, and find that whether there are significant correlations between user behaviors. Furthermore, we will leverage association rule mining technology to extract meaningful behavioral rules, which may help predict the occurrence of user behaviors.

#### Disclosure statement

No potential conflict of interest was reported by the authors.

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# References

- Acs, Z. J., Groot, H. L. F. D., & Nijkamp, P. (2002). The emergence of the knowledge economy: A regional perspective. Berlin: Springer Berlin Heidelberg.
- Ardichvili, A., Page, V., & Wentling, T. (2003). Motivation and barriers to participation in virtual knowledge-sharing communities of practice. *Journal of Knowledge Management*, 7(1), 64–77.
- Aroyo, L., & Kommers, P. (1999). Special issue preface: Intelligent agents for educational computer-aided systems. Journal of Interactive Learning Research, 10(3/4), 235–242.
- Bakeman, R., & Gottman, J. M. (1997). Observing interaction: An introduction to sequential analysis (2nd ed.). Cambridge: Cambridge University Press.
- Chang, H. H., & Chuang, S. S. (2011). Social capital and individual motivations on knowledge sharing: Participant involvement as a moderator. *Information & Management*, 48(1), 9–18.
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982–1003.
- Du, H. S., & Wagner, C. (2007). Learning with weblogs: Enhancing cognitive and social knowledge construction. IEEE Transactions on Professional Communication, 50(1), 1–16.
- Faraj, S., Jarvenpaa, S. L., & Majchrzak, A. (2011). Knowledge collaboration in online communities. *Organization Science*, 22 (5), 1224–1239.
- Fiske, S. T., & Taylor, S. E. (2007). Social cognition: From brains to culture. New York, NY: McGraw-Hill Higher Education.
- Harper, F. M., Li, S. X., Chen, Y., & Konstan, J. A. (2007). Social comparisons to motivate contributions to an online community. In Y. D. Kort, W. Ijsselsteijn, C. Midden, B. Eggen, & B. J. Fogg (Eds.), *Persuasive technology* (pp. 148–159). Berlin: Springer.
- Hawks, I. K. (1987). Facilitativeness in small groups: A process-oriented study using lag sequential analysis. *Psychological Reports*, 61(3), 955–962.
- Hou, H. T., Chang, K. E., & Sung, Y. T. (2008). Analysis of problem-solving-based online asynchronous discussion pattern. Educational Technology & Society, 11(1), 17–28.
- Hou, H. T., Sung, Y. T., & Chang, K. E. (2009). Exploring the behavioral patterns of an online knowledge-sharing discussion activity among teachers with problem-solving strategy. *Teaching and Teacher Education*, 25(1), 101–108.
- Hou, H. T., & Wu, S. Y. (2011). Analyzing the social knowledge construction behavioral patterns of an online synchronous collaborative discussion instructional activity using an instant messaging tool: A case study. *Computers & Education*, 57 (2), 1459–1468.
- Hwang, G. J., & Chen, C. H. (2016). Influences of an inquiry-based ubiquitous gaming design on students' learning achievements, motivation, behavioral patterns, and tendency towards critical thinking and problem solving. *British Journal of Educational Technology*, 22(1), 1. doi:10.1111/bjet.12464

- Lai, C. L., & Hwang, G. J. (2015). A spreadsheet-based visualized mindtool for improving students' learning performance in identifying relationships between numerical variables. *Interactive Learning Environments*, 23(2), 230–249.
- Liang, T. P., Yang, Y. F., Chen, D. N., & Ku, Y. C. (2008). A semantic-expansion approach to personalized knowledge recommendation. *Decision Support Systems*, 45(3), 401–412.
- Lih, A. (2004). Wikipedia as participatory journalism: Reliable sources? Metrics for evaluating collaborative media as a news resource. In *Proceedings of the 5th international symposium on online journalism* (pp. 1–31). Austin, TX.
- Looi, C. K., & Chen, W. (2010). Community-based individual knowledge construction in the classroom: A process-oriented account. *Journal of Computer Assisted Learning*, 26(3), 202–213.
- Milne, D., & Witten, I. H. (2013). An open-source toolkit for mining Wikipedia. Artificial Intelligence, 194, 222–239.
- Paavola, S., Lipponen, L., & Hakkarainen, K. (2004). Models of innovative knowledge communities and three metaphors of learning. *Review of Educational Research*, 74(4), 557–576.
- Puntambekar, S. (2006). Analyzing collaborative interactions: divergence, shared understanding and construction of knowledge. *Computers & Education*, 47(3), 332–351.
- Qiu, G., Liu, B., Bu, J., & Chen, C. (2011). Opinion word expansion and target extraction through double propagation. *Computational Linguistics*, 37(1), 9–27.
- Sackett, G. P. (1978). Observing Behavior: Theory and applications in mental retardation (Vol. 1). Baltimore, MD: University Park Press.
- Shachaf, P., & Hara, N. (2010). Beyond vandalism: Wikipedia trolls. Journal of Information Science, 36(3), 357–370.
- Sun, Z. L. (2011). Study on the knowledge ecological system evolutionary mechanisms. *Journal of Intelligence*, 30(6), 152– 155.
- Sung, Y. T., Hou, H. T., Liu, C. K., & Chang, K. E. (2010). Mobile guide system using problem-solving strategy for museum learning: A sequential learning behavioural pattern analysis. *Journal of Computer Assisted Learning*, 26(2), 106–115.
- Tseng, F. C., & Kuo, F. Y. (2014). A study of social participation and knowledge sharing in the teachers' online professional community of practice. *Computers & Education*, *72*, 37–47.
- Vonderwell, S., & Zachariah, S. (2005). Factors that influence participation in online learning. *Journal of Research on Technology in Education*, 38(2), 213–230.
- Vries, S. D., Bloemen, P., & Roossink, L. (2000). Online knowledge communities. WebNet World Conference on the WWW and Internet, San Antonio (Vol. 2000, No. 1, pp. 124–129).
- Wang, S., Noe, R. A., & Wang, Z. M. (2014). Motivating knowledge sharing in knowledge management systems a quasifield experiment. *Journal of Management*, 40(4), 978–1009.
- Wu, S. Y., Chen, S. Y., & Hou, H. T. (2016). Exploring the interactive patterns of concept map-based online discussion: A sequential analysis of users' operations, cognitive processing, and knowledge construction. *Interactive Learning Environments*, 24(8), 1778–1794.
- Yang, X. M. (2015). The status and problems of learning resource evolution in open knowledge community-taking the case of learning cell knowledge community. *China e-Education*, 11, 45–53.
- Yang, X., Li, J., Guo, X., & Li, X. (2015). Group interactive network and behavioral patterns in online English-to-Chinese cooperative translation activity. *The Internet and Higher Education*, 25, 28–36.
- Yang, X., Qiu, Q., Yu, S., & Tahir, H. (2014). Designing a trust evaluation model for open-knowledge communities. British Journal of Educational Technology, 45(5), 880–901.
- Yi, J. (2009). A measure of knowledge sharing behavior: Scale development and validation. *Knowledge Management Research & Practice*, 7(1), 65–81.
- Yu, S. Q., Yang, X. M., Cheng, G., & Wang, M. J. (2015). From learning object to learning cell: A resource organization model for ubiquitous learning. *Educational Technology & Society*, 18(2), 206–224.
- Zeng, C. X. (2011). Community-based knowledge of Web 2.0 application framework. Journal of Chongqing College of Electronic Engineering, 20(3), 152–154.
- Zhang, S., Liu, Q., Chen, W., Wang, Q., & Huang, Z. (2017). Interactive networks and social knowledge construction behavioral patterns in primary school teachers' online collaborative learning activities. *Computers & Education*, 104, 1–17.
- Zhang, H. F., & Zhao, Y. Y. (2012). The influence factors exploration of sharing behaviors of participants in virtual learning communities. *Distance Education in China*, 13, 67–71.
- Zhao, W., Liang, M., Liu, H. X., & Yu, D. Z. (2013). Study on the sharing mechanism of learning resources driven by communities. *China e-Education*, 12, 75–80.