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Knowledge sharing in online health communities: A social exchange theory perspective

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ABSTRACT

Online health communities (OHC) are becoming valuable platforms for patients to communicate and find support. These communities are different from general online communities. The knowledge shared in an OHC can be categorized as either general (public) or specific (private), and each category is shared in vastly different ways. Using the social exchange theory, we propose a benefit vs. cost knowledge sharing model for OHCs. The benefits are mainly based on Maslow's hierarchy of needs, and the cost includes cognitive and executional costs. We use this benefit vs. cost model to examine how OHC members share general and specific knowledge. Data were collected from 323 users of two well-known OHCs in China and were analyzed using the structural equation model. The results demonstrate that three factors positively impact the sharing of both general and specific knowledge: a sense of self-worth, members' perceived social support, and reputation enhancement. Another factor, face concern, has a negative influence on specific knowledge sharing and a positive influence on general knowledge sharing. Executional cost only negatively impacts general knowledge sharing, and cognitive cost only negatively impacts specific knowledge sharing. This study of OHCs reveals that personal benefits promote knowledge sharing and costs prohibit it. These impacts vary between general knowledge and specific knowledge sharing.

1. Introduction

Worldwide, nearly 4.5% of Internet searches are related to health [15]. In Europe, 41.5% of the population believes the Internet is a good place to find medical information, and 23% actually use the Internet to get medical information [53]. In China, 64% of Internet users visit social-service websites, and health websites are visited most frequently by users — more than 100 million per month between January 2011 and January 2012 [28]. Online communities are important places for people to search for health information and discuss their experiences with medical treatments. Eleven percent of adults in the U.S. have followed their friends' health updates on online communities, and 5% have posted their own information, questions, or comments about health or medical matters [19].

Though OHCs are a valuable platform to share general health knowledge, such as hospital information, drug side effects, and healthy behaviors [45], questions still remain as to what factors determine whether community members' will share their specific knowledge, including their own private medical information.

OHCs make it possible to exchange medical knowledge in many modes, including mailing lists, newsletters, message boards, blogs, discussion forums and social networking sites [5]. OHCs can help connect patients with similar health conditions, so they can share experiences regarding treatments and nutrition regimens [2]. Moreover, OHCs can diminish geographic barriers and provide medical information and social support without specific time limits [4]. OHCs also promote positive behavior. Members' treatment decisions, health expectations and outcomes, and behavioral changes are influenced by their peers in the community [20].

Some previous studies (e.g., [21,35,38,47]) explore users' motivations for sharing health knowledge online. However, these

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studies do not distinguish between general (public) knowledge and specific (private) knowledge. OHCs focus on the exchange of both kinds of health knowledge: general information, such as hospital or doctor information, as well as specific information, such as personal health conditions, medical treatments, and painful medical experiences. General knowledge is normally publicly available and independent of personal health information, but specific knowledge is usually related to patients' privacy. Specific knowledge may be uncomfortable, unpleasant or even painful to share, but it can also be particularly valuable for other community members.

This study considers the different value and impact of specific and general knowledge on OHC members, and examines the factors that influence how both kinds of knowledge are shared. We apply social exchange theory [16] as the theoretical foundation to develop the benefit and cost analysis framework. We focus on the different impacts of community members' perceived benefits and costs on their knowledge sharing behavior. The benefit factors in this research, which are based on Maslow's hierarchy of needs theory [36], include reputation, sense of self-worth, face concern, and social support. The cost factors include cognitive and executional costs.

The paper is organized as follows: Section 2 reviews the theoretical foundation and proposes research hypotheses. Section 3 discusses the research methodology. Section 4 presents the results of our analysis. Section 5 concludes the paper by discussing the contributions of our research, as well as its implications and limitations.

2. Theoretical foundation and research hypotheses

Social exchange theory seeks to explain individual behavior involved in the process of resources exchange [16]. It states that an individual exchanges resources with another individual out of the desire to receive something through contact. From the perspective of social exchange theory, the principle of individual behavior is to maximize benefits and minimize costs. Social exchange theory is widely applied to explain individual behavior across various domains, including information technology adoption [22], consumer behavior [41], information sharing [23], and behavior in online communities [29]. In this research, we use social exchange theory as our main framework to analyze the impact of perceived benefits and costs on knowledge sharing in OHCs.

Maslow's hierarchy of needs theory, which describes the inherent development requirements of individuals [36], identifies five basic universal needs that are essential to human existence. The lower orders in the hierarchy include physiological needs as well as the need for safety, love/belonging, and esteem. The higher-order need is self-actualization. Maslow [36] also proposes that lower needs may take precedence over higher needs. Given its strong and sensible perspective, Maslow's theory provides a valuable framework to analyze the perceived benefits for knowledge sharing in OHCs.

Knowledge sharing is a kind of exchange behavior [6]. Users who share knowledge in OHCs may want to get some return of intrinsic and extrinsic benefits [31]. Intrinsic benefits, such as the feelings of pleasure and satisfaction people experience when they participate in an activity, are intangible and therefore may not be measured directly. Intrinsic benefits motivate individuals to perform certain activities for no other reasons than personal fulfillment and gratification. Extrinsic benefits, by contrast, come from outside an individual in the form of rewards, promotion, coercion, or punishment. The main extrinsic benefits of exchange behavior are economic reward, reciprocal benefits, and reputation feedback.

Knowledge sharing behavior is driven by a combination of intrinsic and extrinsic benefits. OHC contributors who share knowledge may find joy in enhancing their own knowledge or find social value in educating others. They may get money from the community or help other participants benefit from their knowledge. As a result of contributing, OHC members may also enhance their reputation in the community. From the perspective of Maslow's hierarchy of needs theory [36], once the low-level needs (i.e., physiological and safety needs) are basically fulfilled, individuals will attempt to satisfy their needs for love/belonging, esteem, and self-actualization. Social support discussed in health informatics literature [47], which can be categorized into Maslow's love/belonging category [36], represents an OHC member's social need as well as his or her active participation in relationships with other OHC members. Face, an extremely important concept in Chinese culture [27], together with reputation, can be categorized into Maslow's esteem category [36]. Face and reputation represent the need for self-respect and the respect of others. Sense of self-worth describes humans' ultimate need for self-actualization [36]. Based on the intrinsic characteristics of these factors, we define the sense of self-worth as an intrinsic reward of knowledge sharing in OHCs. We define face, reputation, and social support as extrinsic rewards.

Based on social exchange theory [16], we propose the following benefit versus cost research framework in OHCs (Fig. 1) and, by applying Maslow's hierarchy of needs [36], we propose the following knowledge sharing benefit analysis. We hypothesize that individuals' perceived benefits significantly motivate the sharing of general and specific knowledge, and perceived costs diminish their knowledge sharing behavior. Because the focus of this research is on factors that contribute to the sharing of general

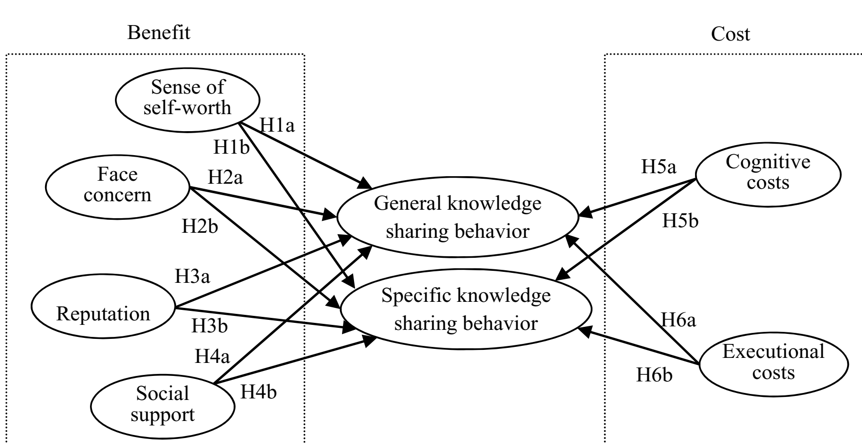

Fig. 1. Knowledge sharing model in online health communities.

and specific knowledge in OHCs, we do not propose hypotheses among the individual benefit constructs.

2.1. Knowledge types

Depending on the purpose of the study and its classification criteria, knowledge can be divided into many categories: explicit and tacit knowledge, personal and organizational knowledge, technology and management knowledge, general and specific knowledge, and so on [37,43,52]. Most previous studies classified knowledge into two dimensions: tacit and explicit. Tacit knowledge is subconsciously understood and applied, yet difficult to articulate. Explicit knowledge is more precisely and formally articulated [27].

OHCs are different from other online communities because the knowledge exchanged is closely related to the physical and mental health of members. The knowledge can be divided into general knowledge and specific knowledge [52] according to whether the knowledge is unique to that patient or not. In OHCs, general knowledge, also referred to as public medical and health knowledge, is often publicly available [52] and easily accessible. This knowledge, which includes hospital information, pharmaceutical prices, and so on, is normally explicit. Specific knowledge, also called private knowledge, depends on context [52]. In the OHC setting, specific knowledge is closely related to an individual's personal experience, such as medical records and reactions to treatment, and includes tacit and explicit knowledge.

OHC community members have no privacy concerns about general knowledge and can share it freely. Learning specific knowledge in an OHC, however, requires a substantial cost [52]. Members usually do not want to share their specific knowledge with others because of privacy issues and the pain of recalling unpleasant medical experiences [11]. Yet sharing specific knowledge is extremely important and valuable for OHC community members in several ways. First, by browsing specific knowledge, users can identify patients with similar symptoms and find appropriate medical treatment for themselves. Second, understanding the experiences of others can give users a better idea of what to expect from their own treatment. Third, sharing specific knowledge can help community members promote healthy behavior and find social support.

Prior literature (e.g., [6,27,32]) on knowledge sharing examines the different influences of explicit knowledge and tacit knowledge, while rarely considering the unique characteristics in OHCs. We aim to explore the difference between general and specific knowledge sharing in the OHC environment.

2.2. Benefits

As discussed in the beginning of Section 2, we propose the following four benefit determinants of knowledge sharing in OHCs based on Maslow's hierarchy of needs [36].

2.2.1. Sense of self-worth

Sense of self-worth describes the extent to which people see themselves as providing value to the community through their knowledge sharing [6]. When people find that sharing knowledge is helpful for others, they become more confident in their personal social status and value, which improves their involvement in the community [10]. From the perspective of human growth needs, the realization of self-worth is the ultimate goal in life [36]. Considering that other community members will benefit greatly from health knowledge sharing — including making better medical decisions and finding support in their recovery — people become more willing to share what they think is helpful in order to achieve self-worth and realize their potential, regardless of whether their knowledge is general or specific. Previous studies also propose and validate that there exists a positive relationship between knowledge sharing and sense of self-worth [6]. Sharing painful specific knowledge can be more difficult than sharing general knowledge, but people will make efforts to do it to realize their self-worth [33]. As a result, the pursuit of self-worth realization will have no difference on specific and general knowledge sharing. Thus, we propose the following hypotheses:

H1a. Sense of self-worth has a positive impact on general knowledge sharing behavior in online health communities.

H1b. Sense of self-worth has a positive impact on specific knowledge sharing behavior in online health communities.

H1c. The impact of sense of self-worth on general and specific knowledge sharing behavior in online health communities is not significantly different.

2.2.2. Face concern

The behavior of individuals in online environments is influenced significantly by national culture [51]. Prior literature finds that culture is one of the most important factors affecting knowledge sharing in a virtual and anonymous environment [24,42]. In Chinese culture, face (*mianzi* in Chinese) is the respect, pride, and dignity that results from an individual's social achievement and practice [34]. Face concern is the extent to which a person has interest in protecting and improving his or her positive social image in social interactions [46]. Face in Chinese society is all-encompassing in its effect on social interaction.

Although anonymity is the general phenomenon of Internet communities, members usually seek to create online identities to identify each other and may engage in various levels of self-expression [48]. Social interaction in online communities is similar to offline communication, which can help users establish a good reputation and gain acceptance and recognition from others. Huang, Davison, and Gu [27] find that face has a positive influence on knowledge sharing. Thus, we propose that face is also important in OHCs.

One important way to protect and gain face is through self-expression, by which an individual displays his or her strengths. If an individual's abilities are recognized by others, he or she will be respected [26]. Knowledge sharing is also a form of self-expression. Sharing general knowledge highlights a contributor's rich experience and wealth of information. Sharing specific knowledge demonstrates the contributor's generosity and kindness. When the general or specific knowledge meets another participant's expectations and helps his or her recovery, the contributor will be praised and gain face. But since specific knowledge of medical history and painful experiences is more private, community members are generally more cautious about sharing it. Thus, we hypothesize:

H2a. Face concern has a positive impact on general knowledge sharing behavior in online health communities.

H2b. Face concern has a positive impact on specific knowledge sharing behavior in online health communities.

H2c. Face concern has a more positive impact on general knowledge sharing behavior than on specific knowledge sharing behavior in online health communities.

2.2.3. Reputation

In this study, reputation refers to an individual's perception of earning respect or enhancing status through participation in an OHC. Users build up their reputations by demonstrating their valuable expertise on diseases, medicine, and medical treatment [9]. A good reputation carries significant mental or physical enjoyment and privileges in society. On the other hand, as a type of personal self-interest, reputation is also a key factor in influencing knowledge sharing [43]. Thus, we propose that good reputation and personal image are the most important factors stimulating participants' knowledge sharing behavior. In addition, a good reputation is not typically built instantaneously, but formed through the consistent demonstration of unique and significant behaviors across various occasions [54]. Therefore, we posit that reputation will have no effect on a single event of general knowledge and specific knowledge sharing. Based on these arguments, we propose:

H3a. Reputation has a positive impact on general knowledge sharing behavior in online health communities.

H3b. Reputation has a positive impact on specific knowledge sharing behavior in online health communities.

H3c. The impact of reputation on general and specific knowledge sharing behavior in online health communities is not significantly different.

2.2.4. Social support

Online communities are virtual social spaces where people come together to obtain and provide information or social support [5]. Online communities can provide medical information and generate social support for anyone affected by disease, which is one of the most important motivation for people to engage in OHCs. These communities also help reduce feelings of isolation, allow users to learn more about symptoms or treatments, and better prepare them for further medical treatment. On the one hand, people share their general knowledge to get other members' recognition, which helps establish friendship among community members. On the other hand, people share their specific knowledge of personal treatment information — as well as discuss their fears and anxieties — to get social support and beneficial information. Communicating this personal information, which generates replies and messages from others, also makes users feel empowered to confront their anxieties, doubts, and fears [7]. Therefore, we posit that to provide or obtain social support, it is much more important to share specific knowledge in OHCs. Individuals may have more incentive to share specific knowledge that will emotionally support others when those members are in despair. Therefore, we have the following hypotheses:

H4a. Social support has a positive impact on general knowledge sharing behavior in online health communities.

H4b. Social support has a positive impact on specific knowledge sharing behavior in online health communities.

H4c. Social support has a more positive impact on specific knowledge sharing behavior than on general knowledge sharing behavior in online health communities.

2.3. Costs

Cost refers to the expenditure made to accomplish something. In social exchange theory, costs are defined as negative outcomes from exchange behavior, and thus reduce the behavior frequency [44]. Before taking an action, rational people will take its positive and negative outcomes into consideration. Previous studies suggest that costs, like benefits, are important factors in determining knowledge sharing [17,31]. People contribute knowledge only if the expected benefits outweigh the costs [6].

Specifically, costs can come in cognitive and executional forms [44]. Psychologists propose that individuals have to cognitively process a great deal of information about an environmental stimulus before physically responding to it [18]. In order to contribute to an OHC, a member needs to cognitively retrieve his or her memory of general or specific knowledge. We call this cognitive cost. This cognitive process is extensive, and patients may recall their pain and uncomfortable feelings, which produces negative psychological effects such as irritation, depression, and panic. This complex cognitive process will diminish knowledge sharing, especially for specific knowledge, which results from unhappy experiences of personal treatment. Therefore, we propose that:

H5a. Cognitive costs are negatively related to general knowledge sharing behavior in online health communities.

H5b. Cognitive costs are negatively related to specific knowledge sharing behavior in online health communities.

H5c. Cognitive costs have a more negative impact on specific knowledge sharing behavior than on general knowledge sharing behavior in online health communities.

Executional costs include the time, material, and financial resources that individuals commit when they engage in certain activities. OHC users need to codify their tacit opinions before posting and replying to messages online. This process requires significant amounts of time and energy, regardless of whether they will share general or specific knowledge. Given that this time and effort could be used to engage in alternative behavior (and accrue its corresponding rewards), they are considered contribution costs [3]. Previous studies have shown that when the knowledge contribution requires significant time, sharing tends to be inhibited [39,44]. Although the sources of general and specific knowledge are different, the codifying and publishing effort of them is similar in the OHCs. Therefore, we assume that:

H6a. Executional costs have a negative impact on general knowledge sharing behavior in online health communities.

H6b. Executional costs have a negative impact on specific knowledge sharing behavior in online health communities.

H6c. The impact of executional costs on general and specific knowledge sharing behavior in online health communities is not significantly different.

3. Methods

3.1. Instrument development

Based on our research model, we developed a survey questionnaire to measure the proposed constructs that may contribute to knowledge sharing behavior in OHCs. To measure each construct, questions were compiled and adapted from validated instruments used in the prior literature, and the wording was modified to fit the Chinese OHC context. Specifically, we adapted items for sense of self-worth (SSW) from Bock et al. [6]; face concern (FC) items from Wan [46] and Huang, Davison, and Gu [27]; items for general knowledge sharing (GKS) and specific knowledge sharing (SKS) from Hsu et al. [25]; items for reputation (R) from Chang and Chuang [9]; social support (SS) items from Xiao [49]; cognitive cost (CC) and executional cost (EC) items from Tong, Wang and Teo [44]. We conducted a backward translation process to ensure consistency between the Chinese and English versions of the instrument [6,27], and rated all items using a seven-point

Likert scale, with 1 indicating "strongly disagree" and 7 indicating "strongly agree."

To assess the construct validity of the various items, we attempted to identify any that might be ambiguous through two methods: expert review and a pilot study.

In the expert review stages, we invited two groups of experts to separately discuss their understanding of the questionnaire items and comment on whether those items accurately reflected the theoretical constructs. The first panel of experts was comprised of three professors from different Chinese universities. Each was familiar with the survey research methodology and had been engaged in knowledge sharing research. They reviewed the writing style and made comments on any unclear items. The experts in the second group were 10 reviewers with rich experience in OHCs who acted as judges to evaluate the questionnaire's feasibility in Chinese OHCs. Each item was discussed and ambiguous items were marked and revised. Experts also double checked the structure and format of the original questionnaire, including a variety of statements. We removed some items that were reported to be indigestible, ambiguous, or that didn't represent the constructs well.

After the initial survey refinement, we conducted a pilot test with 82 responses to ensure that the instrument had acceptable reliability and validity. SPSS Statistics Version 20 was used to check the reliabilities. Cronbach's α of each variable, as well as the entire questionnaire, was greater than the recommended 0.70 level.

Moreover, we performed exploratory factor analysis to measure convergent and discriminant validity of the items. We first checked KMO (Kaiser–Meyer–Olkin Measure of Sampling Adequacy) and Bartlett's test of sphericity, and the results showed that the collected data was suitable for factor analysis.

Then, we measured the validity of the questionnaire by checking the factor loadings, cross loadings, and the average variance extracted (AVE). The factor loadings for each indicator on its corresponding construct were greater than 0.70 and higher than the factor loadings on other constructs, thus supporting convergent validity. For each construct, the average variance extracted was greater than 0.5, suggesting that the explained variance was more than the unexplained variance [40].

The final questionnaire contained thirty-eight questions, eight of which were related to personal information.

3.2. Data collection

To test our research hypotheses, we collected data through two major OHCs in China: Phoenix Health (http://fashion.ifeng.com/health/) and Sweet Home (http://bbs.tnbz.com/). According to Alexa, Phoenix ranks 33rd amongst Chinese websites, and the daily page views per visitor reach 6.40. Discussions on Phoenix Health cover a variety of diseases. Sweet Home, with nearly 130,000 members, focuses on diabetes and provides a communication platform for diabetic patients.

The website administrators of these two OHCs posted and highlighted our survey questionnaire and an invitation to participate. In order to inspire community members' involvement, we offered a gift valued at $3 to each respondent. Furthermore, ten respondents were randomly selected to be awarded a $25 cash bonus. The data collection procedure took place from August 31 to September 30, 2013. We received 347 questionnaires and discarded 24 that were incomplete, resulting in 323 valid questionnaires.

4. Results

4.1. Descriptive statistics

Table 1 summarizes the demographic information of the 323 respondents. We also conducted independent-sample *T*-tests to examine whether there exists group differences between the respondents from the two websites. The results show no significant different in the age, gender, length of participation in OHCs, and educational background of respondents. Sixty-three percent of respondents were female, which is consistent with findings from previous studies [14,47]. It is also representative of the gender distribution of the Phoenix Health community, where 61% of registered users are female. This is consistent with prior literature that women tend to use online communities much more than men [1]. Of these sample users, 49% have online health community experience of more than one year.

Table 1
Demographic profile.

Variable	Sample	Percentage (%)
Gender		
Male	119	36.84%
Female	204	63.16%
Age (years)		
<18	7	2.17%
18–25	43	13.31%
26–35	109	33.75%
36–45	57	17.65%
46–60	83	25.70%
>60	24	7.43%
Length of participation in OHCs		
<4 months	59	18.27%
4–12 months	106	32.82%
13–24 months	29	8.98%
25–36 months	40	12.38%
>36 months	89	27.55%
Education		
Below high school	19	5.88%
High school	59	18.27%
Bachelor's degree	176	54.49%
Master's degree	69	21.36%

The age of participants ranged from 22 to 60 years old, while about 67% of participants were younger than 45 and 7% were older than 60. The average age of OHC users is higher than general online communities [13]. The number of older people using the Internet has been increasing in recent years, and they may be willing to search for health information using OHCs [12]. People with higher education levels tend to use OHCs more often for health information [1,30].

4.2. Data analysis

We used a structural equation model to analyze the determinants of knowledge sharing in OHCs. To check the measurement model, we first performed confirmatory factor analysis, which focuses on the evaluation between constructs and their variables. We then examined the structural relationships.

We first evaluated the measurement model by LISREL 8.8 via confirmatory factor analysis, testing the construct unidimensionality, convergent, and discriminant validity of the constructs and its items. Consistent with structural equation modeling recommendations, we used covariance matrices of observed variables as input, and assessed overall fit based on χ^2 goodness-of-fit test, GFI (goodness-of-fit index), AGFI (adjusted goodness-of-fit statistic), CFI (comparative-fit index), NFI (normed-fit index), SRMR (standardized root mean square residual), and RMSEA (root-mean-square error of approximation). The confirmatory factor analysis results support that the measurement model fits the data well, $\chi^2 = 631.71$, $\chi^2/df = 1.68$, GFI = 0.88, AGFI = 0.86, CFI = 0.98, NFI = 0.96, SRMR = 0.031 and RMSEA = 0.046. All the model-fit indices exceed the normal common acceptance levels, indicating that the measurement model has a good fit with the collected data.

Table 2
Construct statistics and factor correlations ($N = 323$).

Construct	Mean	SD	GKS	SKS	FC	SSW	SS	EC	CC	R
GKS	4.07	1.36	**0.89**							
SKS	3.84	1.30	0.42	**0.88**						
FC	4.07	1.59	0.40	−0.16	**0.88**					
SSW	4.19	1.57	0.55	0.55	0.13	**0.91**				
SS	4.32	1.58	0.43	0.41	0.15	0.24	**0.91**			
EC	4.06	1.51	−0.07	−0.07	−0.01	−0.04	−0.06	**0.87**		
CC	4.20	1.62	−0.40	−0.40	0.23	0.08	−0.09	0.05	**0.90**	
R	4.11	1.57	0.41	0.38	0.09	0.15	0.29	0.11	−0.04	**0.91**

Table 2 shows the means, SDs for the variables, and the correlations between the constructs. Table 3 shows the confirmatory factor analysis results of the measurement model. The resulting Cronbach's α of each construct exceeds the recommended 0.70 level and the composite reliability is greater than 0.70, indicating good reliability. All indicator loadings are significant and greater than 0.70, assuring the convergent validity of the measurement model. We calculated average variance extracted (AVE) value of each variable through the factor loadings measured, and they all were greater than 0.50. In Table 2, the main diagonal value is the square root of AVE and the non-main diagonal is the correlation coefficient between the constructs. All the diagonal values are greater than 0.7 and exceed the correlations between any pair of constructs. That value indicates that the model also has adequate discriminant validity.

We also conducted an exploratory factor analysis and applied Harmon's one-factor test to assess if common method bias would be a problem [8]. The exploratory factor analysis result of the 30 variables is given in Appendix B. The 8 factors could explain 85.556% of the total variance with the first factor accounting for the highest variance of 26.075%. No single factor could explain most of the covariance among the measures, which indicates that common method bias was not a serious threat in our study.

The hypotheses presented earlier were tested within a structural equation modeling (SEM) framework using LISREL, which accounts for all the covariance in the data and provides more accurate parameter estimations than other techniques. The results of fitting the structural model to the data indicate that the model has a good fit with a relatively low χ^2 (Table 4). Most other measures of fit, including χ^2 per degree of freedom, were in the acceptable range and above the minimum recommended values. Only GFI and AGFI were in the margin. The completely standardized path coefficients of the structural model provide evidence for the hypothesized relationships and are shown in Fig. 2.

Table 3
Confirmatory factor analysis results of the measurement model.

Construct	Item	Standardized estimates	*T*-value	AVE	CR	α
GKS	GKS1	0.94	22.44	0.80	0.94	0.89
	GKS2	0.87	19.59			
	GKS3	0.88	20.01			
	GKS4	0.89	20.32			
SKS	SKS1	0.94	22.37	0.78	0.94	0.91
	SKS2	0.87	19.4			
	SKS3	0.86	18.97			
	SKS4	0.87	19.43			
FC	FC1	0.91	20.86	0.78	0.93	0.83
	FC2	0.85	18.66			
	FC3	0.88	19.62			
	FC4	0.89	20.03			
SSW	SSW1	0.92	21.17	0.82	0.93	0.90
	SSW2	0.87	19.41			
	SSW3	0.93	21.71			
SS	SS1	0.94	22.26	0.82	0.93	0.88
	SS2	0.9	20.48			
	SS3	0.88	19.73			
EC	EC1	0.89	20.08	0.76	0.94	0.82
	EC2	0.81	17.26			
	EC3	0.89	20.14			
	EC4	0.9	20.66			
CC	CC1	0.93	21.63	0.81	0.94	0.86
	CC2	0.88	19.7			
	CC3	0.91	20.98			
	CC4	0.87	19.57			
R	R1	0.92	21.56	0.82	0.95	0.92
	R2	0.89	20.38			
	R3	0.91	20.86			
	R4	0.9	20.6			

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Table 4
Goodness of fit assessments for the structural model.

Goodness of fit measures	χ^2(df)	χ^2/df	GFI	AGFI	CFI	NFI	SRMR	RMSEA
Goodness of fit ranges	Non-sign.	<2	>0.9	>0.9	>0.95	>0.9	<0.08	<0.05
SEM model	674.02 (383)	1.76	0.88	0.85	0.98	0.95	0.068	0.049

To test Hypotheses H1c, H2c, H3c, H4c, H5c and H6c, we adopted the method suggested by Xu [50]. For each hypothesis, we used an alternative model by constraining that the two relationships in the hypothesis have the same value. Then, we evaluated the statistical difference between the alternative model and original hypothesized model using a *t*-test to compare their path coefficients.

Fig. 2 summarizes the completely standardized path coefficients of the structural equation model and depicts the significant predictors of knowledge sharing behavior.

In summary, hypotheses H1a and H1b, predicting a positive relationship between sense of self-worth and knowledge sharing behaviors (both general and specific), are supported. There is no significant difference between the impact of sense of self-worth on general and specific knowledge sharing behavior, so H1c is also supported.

In Hypotheses H2a and H2b, we initially proposed that face concern would have a positive relationship on both general and specific knowledge sharing. However, our results reveal a positively significant relationship between face concern and general knowledge sharing (H2a), but a negatively significant relationship between face concern and specific knowledge sharing (H2b). Therefore, H2a is supported, but H2b is not supported. We initially proposed H2b because we reasoned that gaining "face" may make OHC members share specific knowledge. However, it seems that we underestimated the potential to lose "face" if an OHC member reveals his or her medical history. From this perspective, it is not surprising that H2b is not supported (in fact, completely contrary to H2b, we found a significant relationship that face concern negatively affects specific knowledge sharing).

H2c proposes that OHC members may naturally share more general knowledge than specific knowledge due to privacy concerns (face concern). Given the aforementioned situation, our test finds that H2c is still supported. Moreover, we find that reputation and social support are important determinants of both types of knowledge sharing in OHCs. Thus, H3a, H3b, H4a and H4b are all supported.

While we find that the impact of reputation on both general and specific knowledge sharing is not significantly different, we do not find any support for our proposition that social support has a more positive impact on specific knowledge sharing. Consequently, H3c is supported, but H4c is not supported.

In Hypotheses 5 and 6, we propose cognitive costs and executional costs have a negative impact on both general and specific knowledge sharing. However, we only find a significant relationship between cognitive costs and specific knowledge sharing behavior (H5b), and between executional costs and general knowledge sharing behavior (H6a). So, H5b and H6a are supported, while H5a and H6b are not. These results indicate that different types of costs have effects on different types of knowledge sharing. The explanation could be as follows: Since specific knowledge is more about an OHC member's personal medical experience, it requires more cognitive costs to process prior to sharing. The executional costs are negligible compared to the unpleasant emotions resulting from specific knowledge sharing. On the contrary, sharing general knowledge, such as a hospital's address, working hours or wait times, does not require additional cognitive costs. Therefore, executional cost (e.g., spending time to codify the information) is more salient to general knowledge sharing. Furthermore, there are significantly larger cognitive costs for specific knowledge than for general knowledge sharing, so H5c is supported. Contrary to our hypothesis, there is a significant difference between the impact of executional costs on general and specific knowledge sharing. Thus, H6c is not supported.

5. Discussion

5.1. Primary findings and theoretical contributions

The knowledge sharing actions among members of online health communities directly affect the operation and success of those communities. However, there has been limited research on the determinants of knowledge sharing in OHCs, and prior literature did not take the unique characteristics of different types of knowledge into consideration. In this study, we used social exchange theory to examine how OHC users' knowledge sharing behavior is affected by reputation, face concern, sense of self-worth, social support, and sharing costs.

This research makes several contributions. First, it is among the first to explore differences between specific and general knowledge sharing in OHCs. Specific knowledge is more valuable

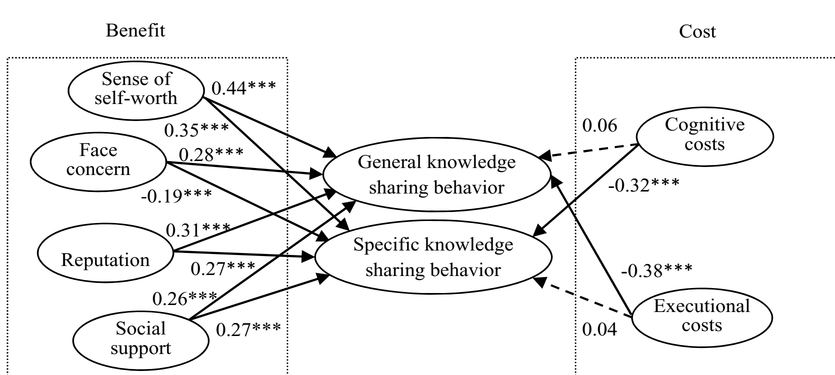

Fig. 2. Path coefficients and significance levels. $^{*}p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$.

for patients, but is much more difficult to share. Our results show that specific and general knowledge sharing in OHCs are influenced by different factors. Second, our research makes an important first step toward exploring the knowledge sharing mechanisms of Chinese OHCs, which can help promote further sharing of health knowledge in China. Third, we investigate the impact of Chinese culture (i.e., face concern) on the sharing of different kinds of health knowledge in OHCs. The empirical results demonstrate that face concern impacts health knowledge sharing in OHCs. Fourth, we apply the social exchange theory to the sharing of health knowledge in Chinese OHCs, and extend the theory to a new research setting. The results show that the social exchange theory can be generalized to explain the relationship between certain antecedents and health knowledge sharing behavior. Fifth, our research investigates the effect of costs, the essential elements of social exchange theory, on the two types of health knowledge. Our results demonstrate that, depending on the type of knowledge sharing, costs do not always prohibit sharing.

Based on the benefit and cost analysis, our research demonstrates that it is valid and essential to distinguish between general and specific knowledge in OHCs because there are vast differences in sharing costs and certain benefit determinant for each type. The knowledge acquisition procedure is more complex and the cost is much higher for specific knowledge compared to general knowledge. Therefore, there are significantly higher barriers to specific knowledge sharing in OHCs.

Reputation, social support and sense of self-worth have a positive effect on general and specific knowledge sharing, indicating that an individual's need for growth and self-realization can encourage sharing, regardless of knowledge type.

Face concern is related to knowledge sharing [27], yet little is known about the impact it has on sharing different types of health knowledge. Our results demonstrate that face concern promotes the sharing of general knowledge but inhibits the sharing of specific knowledge. OHC members are much more willing to share general knowledge because it can help them gain face. However, sharing specific, personal knowledge can be embarrassing, and may cause one to lose face. Face concern and reputation seem to be closely related, but our research shows that they have the opposite impact on specific knowledge: reputation has a positive effect, and face concern has a negative effect.

The influence of executional and cognitive costs on knowledge sharing varies. Executional cost is the major consideration for sharing general knowledge, while cognitive cost is the major consideration for sharing specific knowledge. It is more simple and convenient to acquire general knowledge than specific knowledge. Members spend less time and effort sharing general knowledge and this time and effort is the primary investment. Specific knowledge is difficult and often unpleasant to obtain, and emotions are the biggest obstacle to sharing. Members may not want to relive the memory of their diagnosis, treatment and recovery, and so they may resist the process of sharing specific knowledge.

5.2. Practical implications

In addition to the research contributions discussed in Section 5.1, this study also sheds light on OHC's practical applications.

First, an OHC should align management and incentive policies with the type of knowledge that will be shared in its community. Communities focusing on general health knowledge should promote personal self-realization to reduce the sharing cost. Communities focusing on specific health knowledge should promote privacy protection as well as personal self-realization.

Second, every person — whether healthy or sick — has a different way of satisfying the universal need for self-realization. Therefore, OHCs must inspire members to participate by setting up mechanisms and regulations that facilitate personal growth. For example, OHCs might establish a credit-and-rating promotion system for users, invite health experts to join the community, or organize offline activities.

Third, OHCs should allay members' concerns about specific knowledge sharing with the help of advanced IT and management mechanisms. For example, OHCs might enable members to restrict access to the private knowledge that they share. To support this, communities should also establish punitive regulations for behavior that discourages the sharing of specific knowledge.

Fourth, the quality of the sharing platform influences both kinds of knowledge sharing. The user interface should be easy to understand. To enhance the sharing of specific knowledge, the environment should be friendly and pleasant. For example, the sharing process could be accompanied by inspirational music. The OHC should publicize the impact that results from members sharing their specific knowledge, as well as encourage members to rate one another's knowledge and share their success stories.

5.3. Limitations

Our study has several limitations that provide opportunities for future research. First, our study is based on a cross-sectional survey; we did not take the longitudinal factor into consideration. Although the reliability and validity checks ensure the research's robustness, future studies could consider longitudinal research designs to narrate the relationship between knowledge sharing and related determinants.

In addition, the sample does not represent all health communities. We used an online survey to collect data, and this may be biased toward those who are familiar with information technology or those who are healthier and able to complete the survey. Future studies could consider other surveying and sampling strategies.

Third, our hypothesized model successfully uses benefit vs. cost to analyze knowledge sharing, but there may be other important factors. Future research could expand upon our findings to include characteristics such as risk and trust, which prior work has shown to predict knowledge sharing. Future studies could also divide our face concern construct into face gaining and face saving and explore the influence of these variables. Moreover, researchers could examine other relational constructs in the environmental and cultural dimensions, such as subjective norms, mutual influence, and *guanxi* (relationship).

Finally, this study did not consider the type of online health community, yet different communities may exhibit different knowledge sharing properties. Hence, the generalizability of the results is limited. Future works can shed light on more types of OHCs.

5.4. Conclusions

This study has provided insights into knowledge sharing in online health communities: to encourage knowledge sharing, it is important to increase benefits and decrease costs for users. This reinforces results from related research in health and knowledge management. In addition, we demonstrate that general knowledge and specific knowledge have different influencing factors, which is relevant to both health informatics literature and health community management. We show that multiple predictors, including Chinese culture, can have a significant impact on knowledge sharing, and we make several recommendations to mitigate concerns and promote knowledge sharing by creating policies that tailor online communities to the specific type of knowledge being shared. Finally, we suggest that efforts to promote knowledge sharing should encourage people to realize their self-worth and gain social support.

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Appendix A. Questionnaire: Measured items

Sense of Self-Worth

SSW1: My knowledge sharing would help other members in the online health community solve problems.
SSW2: My knowledge sharing would bring positive influence on other members in the online health community.
SSW3: My knowledge sharing would bring all my facilities into full play and make me more confident.

Face Concern

FC1: I care about others' attitudes toward me.
FC2: I am usually very particular about the way I dress because I do not want others to look down on me.
FC3: Sharing knowledge with other memebers in the online health community will make me gain face.
FC4: I will gain face if I have latest health knowledge.

General Knowledge Sharing

GKS1: When participating in this online health community, I usually actively share some public information I know, including hospital information, medicine price, and so on.
GKS2: When discussing problems related with hospital, medicine and other public issues, I usually involved in the subsequent interactions.
GKS3: I usually spend a lot of time conducting general knowledge (e.g. hospital and medicine information) sharing activities in the online health community.
GKS4: I frequently participate in general knowledge (e.g. hospital and medicine information) sharing activities in the online health community.

Specific Knowledge Sharing

SKS1: When participating in the online health community, I usually actively share my personal health information, including treatment experience, health problem, and so on.
SKS2: When discussing problems related with medical treatment, medical experience and other private issues, I am usually involved in the subsequent interactions.
SKS3: I usually spend a lot of time conducting specific knowledge (i.e. personal medical issues) sharing activities in the online health community.
SKS4: I frequently participate in specific knowledge (i.e. personal medical issues) sharing activities in this online health community.

Reputation

R1: Sharing knowledge can enhance my reputation in the online health community.
R2: I get praises from others by sharing knowledge in the online health community.
R3: I feel that knowledge sharing improves my status in the online health community.
R4: I can earn some feedback or rewards through knowledge sharing that represent my reputation and status in the online health community.

Social Support

SS1: Through knowledge sharing in online health communities, I pour out my troubles and feel relaxed.
SS2: Through knowledge sharing in online health communities, I get some understanding, help or supports from other participants in the community.
SS3: Through knowledge sharing in online health communities, I get comfort and care from other participants in the community.

Executional Cost

EC1: I can't seem to find the time to share knowledge in the online health community.
EC2: It is laborious to share knowledge in the online health community.
EC3: It takes me too much time to share knowledge in the online health community.
EC4: The effort is high for me to share knowledge in the online health community.

Cognitive Cost

CC1: It is annoying to recall every detailed aspect of my or others' medical experience in order to share knowledge in the online health community.
CC2: It is not enjoyable to recall my or others' medical treatment procedure in order to share knowledge in the online health community.
CC3: It is hard for me to recollect medical experience and treatment solution.
CC4: It is costly to organize my or others' medical experiences cognitively for knowledge sharing in the online health community

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Appendix B. Result of exploratory factor analysis

	Component							
	1	2	3	4	5	6	7	8
GKS1	.177	.055	.252	-.216	.213	.762	.296	.195
GKS2	.203	-.020	.265	-.236	.180	.717	.250	.196
GKS3	.213	.081	.213	-.171	.173	.787	.246	.145
GKS4	.232	.066	.152	-.223	.200	.786	.214	.167
SKS1	.197	-.196	-.136	.056	.840	.137	.199	.172
SKS2	.127	-.159	-.097	.058	.851	.147	.119	.138
SKS3	.192	-.241	-.076	.040	.790	.153	.137	.170
SKS4	.149	-.218	-.034	.015	.832	.154	.188	.123
FC1	.009	.073	.897	.043	-.090	.195	.047	.023
FC2	.095	.043	.890	-.052	-.068	.064	.069	.058
FC3	.021	.173	.873	.014	-.108	.138	.049	.022
FC4	.010	.089	.902	.012	-.016	.139	.009	.085
SS1	.122	-.066	.105	.030	.194	.135	.104	.899
SS2	.107	.006	.042	.068	.146	.154	.077	.903
SS3	.119	-.043	.048	.005	.145	.141	.017	.900
SSW1	.043	.016	.043	-.003	.153	.190	.905	.110
SSW2	-.019	.009	.073	-.012	.163	.206	.889	.003
SSW3	.087	-.050	.052	-.019	.202	.218	.887	.081
EC1	.053	.015	.008	.893	-.007	-.185	.036	.037
EC2	.022	-.049	.052	.868	.101	-.090	-.049	-.014
EC3	.043	.052	-.025	.904	.023	-.135	.001	.015
EC4	.092	.064	-.026	.912	.014	-.084	-.028	.062
CC1	.028	.908	.094	.026	-.203	.070	-.029	.003
CC2	.017	.887	.096	.014	-.161	.095	-.018	-.023
CC3	-.063	.918	.075	.030	-.142	-.023	.034	-.023
CC4	-.011	.895	.101	.014	-.136	-.015	-.006	-.054
R1	.910	-.040	.003	.070	.156	.135	.016	.079
R2	.891	-.014	.027	.053	.138	.125	.024	.118
R3	.901	.006	.084	.036	.130	.145	.031	.105
R4	.906	.010	.031	.062	.122	.126	.055	.064

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