THE INFLUENCE OF SOCIAL SUPPORT NETWORKS ON HEALTH CONDITIONS VIA USER ENGAGEMENT: GENDER AS A MODERATOR

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ABSTRACT

There are extensive empirical studies on online health communities (OHCs)—important platforms that help users manage their health conditions. However, little research has concentrated on the role of social support networks and user engagement. This paper aims to investigate the influence of social support networks on users' health conditions via user engagement in health tasks, alongside the moderating effects of gender differences. We established a two-equation model using the data of 1,129 users in an OHC. The empirical results of our research model reveal that the size of a social support network, as well as individual activities and group member activities within the network, are positively associated with levels of user engagement in online health tasks. This paper also finds that the interactive relationship between three factors—(1) the association of social support network size and (2) individual user activities with (3) levels of user engagement—is complementary; further, it finds that the relationship between (1) social support network size, (2) group member activities, and (3) levels of user engagement is substitutable. Moreover, we observe that levels of user engagement in health tasks are positively related to users' health conditions. In addition, our results show the moderating effects of gender differences on the relationship between social support, levels of user engagement in health tasks and user health conditions. The findings of this paper add value to the literature on OHCs and provide some insights into the management of OHCs for practitioners.

Keywords: Online health community; Social support network; User engagement; Gender differences; Health condition.

1. Introduction

Health management is one of the most important service industries in China. However, according to a nutrition and chronic diseases report for China's residents,[1] China has the highest number of people with chronic diseases (more than 300 million patients). Further, 30.1% of Chinese adults are overweight and the country has an obesity rate of 11.9%, making the health forecast for Chinese residents less than optimistic. China is rapidly becoming the second most obese country in the world, after the United States. Finding a way to manage residents' health conditions and to enhance the efficiency of health management has become a pressing issue for Chinese society.

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[1] http://www.nhfpc.gov.cn/jkj/s5879/201506/4505528e65f3460fb88685081ff158a2.shtml

Online health communities (OHCs) are regarded as potential solutions to the issues identified above. With the development of information technology, OHCs have become a way for people to manage their own health. These digital communities are very important for individuals who need to control and manage their health. Generally, health-management tasks (including exercise and dietary plans) launched by OHCs help users to lose weight in a scientific and appropriate way (see Appendix A). When users engage in online health tasks, they can create a self-care model, which allows them to manage their own health conditions. Users can improve their health conditions by accomplishing the health tasks launched by the OHCs. High levels of user engagement in health tasks also improve the interactions between OHCs and users. However, it is still unclear whether engaging in health tasks launched by OHCs can really assist users to lose weight and enhance the efficiency of their health management. Therefore, investigating the role of user engagement in health tasks is a vital research question.

As a result of a lack of appropriate motivators, engaging in health-management tasks can be difficult and stressful for users of OHCs. A major problem for designers is deciding how to improve the levels of engagement in health tasks. OHCs also function as a social platform, where users can develop social support networks and establish social relationships with other users. Social support networks are networks of online communities that help users to interact with other individuals. Users may use these networks to share health-related information, as well as their experiences and knowledge, thus providing social support for one another. Previous studies have proven that social support can assist people to cope with stressful events and can positively affect their behaviors (Yan & Tan, 2014; Zhijun Yan, 2016). Although social support may be useful for individuals, it is difficult for OHC designers to manage and control. New methods should be employed to improve social support for users. Social support theory observes that having a social support network is essential for obtaining actual social support (Balaji et al., 2016)—a factor that can be easily controlled and managed by the designers of OHCs. Understanding the role of social support networks helps the designers of OHCs in the development of new systems and mechanisms. Therefore, investigating the effect of social support networks on OHCs is a valuable research pursuit.

Additionally, since every individual has different psychological needs (Sun et al., 2010), the roles of social support networks and the effects of user engagement in health tasks could vary significantly for different individuals. This paper examines the effects of gender differences on user behavior in OHCs. Gender is one of the most fundamental differences between individuals (Zhou et al., 2014). For example, men and women exhibit different behaviors as a result of different motivations and social needs. Thus, the roles that social support networks and user engagement play for male and female users may differ significantly. Understanding the different needs and behaviors of different genders can assist designers and practitioners of OHCs in implementing different strategies that cater to the needs of different genders (Zhang et al., 2018; Zhou et al., 2014).

Overall, this paper aims to investigate the influence of social support networks on user health conditions via the monitoring of user engagement in health tasks, while seeking to understand the moderating effects of gender differences. This paper attempts to answer the following questions:

1. What are the effects of OHC social support networks on the level of user engagement in health tasks?
2. Is the level of user engagement in health tasks associated with an improvement in user health conditions?
3. Do gender differences moderate the relationship between social support networks, user engagement in health tasks and user health conditions?

Based on social support theory and gender difference theory, this paper has created a two-equation model. We obtained data from 1,129 users of an OHC in China to test our hypotheses on the roles of social support networks, user engagement in health tasks, and gender differences. Our empirical results demonstrate that the features of social support networks in the OHCs (i.e., the size of the social support network, individual activities, and group member activities) positively affect the level of user engagement in online health tasks. This paper also finds that the size of the social support networks and the individual user activities have a complementary relationship, while the size of the social support networks and the group member activities have a substitutable relationship. Further, we show that the levels of user engagement in online health tasks are associated with the improvement of user health conditions, and that gender differences moderate the relationship between social support networks, user engagement, and user health conditions.

This paper contributes to the existing literature in three ways. First, it investigates the role of social support networks on OHCs from the perspective of the networks' structures and activities. Second, it examines the antecedents and consequences of user engagement in online health tasks. Third, combining social support theory and gender difference theory, it explores the effects of gender differences on the relationship between social support networks, user engagement, and health conditions. Its findings provide further insights and suggestions for users and practitioners of OHCs.

The structure of this paper is as follows: Section 2 reviews the prior literature on OHCs, user engagement, social support theory, and gender difference theory. Section 3 discusses the research model and hypotheses. The empirical results are analyzed in Section 4. Section 5 discusses the theoretical implications, practical implications, limitations, and future research directions. Finally, the conclusion of this paper is delivered in Section 6.

2. Literature review

2.1. Online health communities

With the advancement of Web 2.0 technologies, OHCs provide a safe and convenient platform for users to interact with other people (Ziebland et al., 2004). OHCs are a new type of online community (Yan & Tan, 2014; Zhijun Yan, 2016), wherein people provide support for one another, share information, and obtain related health services (Wu, 2016; Zhang et al., 2017). These virtual communities are regarded as potential ways to solve the problem of growing health demands in our society. An increasing number of studies have explored three different empirical aspects of OHCs: 1) User motivations for participating in OHCs, 2) interaction between patients and doctors, and 3) user self-care and health conditions. Table 1 shows a review of related studies on OHCs.

Table 1: Studies on online health communities

Perspectives	Authors	Variables	Research content
User motivation to participate in OHCs	Xiao et al. (2012)	Access to the Internet, trust, and communication quality.	Examining the factors that effect users' online health-related information searches based on the analysis of a national cancer-related survey.
	Ba and Wang (2013)	Online activities, social support, and pay.	Investigating the effects of motivational mechanisms on users' exercise activities in OHCs.
	Bansal et al. (2010)	Privacy, information sensitivity, and personal dispositions.	Investigating the effects of personal dispositions on privacy and information sensitivity when disclosing health information online.
	Yan et al. (2016)	Benefits, cost, and knowledge sharing behavior.	Based on social exchange theory, examining how users share general and specific knowledge in OHCs.
Interaction between patients and doctors	Yang et al. (2015b)	Patient-generated information and system-generated information.	Investigating how patients select a suitable physician according to patient-generated and system-generated information.
	Yang et al. (2015a)	The service delivery process, disease risk, and satisfaction.	Studying the effect of service delivery processes on user satisfaction, as well as the moderating effect of disease risk.
	Liu et al. (2016)	Individual reputations and organizational reputations.	Investigating the effects of the individual and organizational reputations of doctors on the number of appointments in a hospital.
	Wu et al. (2016)	Doctors' reputations and the number of posts.	Examining how doctor reputations affect the odds of patients posting about their experiences.
Self-care and health conditions	Yan et al. (2014)	Informational support and emotional support.	Studying how social support in OHCs can improve users' mental health conditions.
	Ballantine et al. (2011)	Social support.	Examining the effects of social support in OHCs on user weight loss.
	Fox et al. (2005)	Expert patients.	Researching the influence of expert patients on other patients' health conditions.
	Hwang et al. (2010)	Social support and weight loss.	Examining the effects of social support in OHCs on user weight loss.

Although extensive studies have already investigated user self-care and health conditions in OHCs, previous studies focus mainly on the role of social support and overlook the effects of social support networks. Social support networks are the antecedents of obtaining social support; they also determine the amount of social support received. Understanding the role and influence of social support networks can help users obtain actual social support from OHCs. In addition, while much research has examined the motivation behind user participation in OHCs, not many papers have investigated the influence of user engagement on health conditions. To address those research gaps, this paper explores the influence of social support networks and user engagement in OHCs on user health conditions.

2.2. User engagement in online communities

With the development of social media and online communities, scholars have begun to explore the effects of user engagement. The focus has mainly been in the area of online brand communities. Understanding the concept of user engagement and its role is vitally important for both scholars and practitioners when seeking to influence user behaviors and satisfaction (Li et al., 2016; Martínez-López et al., 2017). Although extensive studies have investigated the role and utility of user engagement in online communities, the definition of user engagement is still imprecise and inconsistent.

In general, user engagement can be understood from several perspectives (Wu et al., 2018). For example, Brodie et al. (2013) define user engagement as a comprehensive concept that includes emotional and behavioral dimensions. In addition to this definition, user engagement can be conceptualized in three ways. First, it relates to an individual's psychological state, which will affect the degree to which that individual will interact with communities. Baldus et al. (2015) conceptualized a measure of user engagement whereby motivational mechanisms affect users' interactions in an online community, and Patterson and Yu (2006) define user engagement as a psychological state relating to brands and companies. Second, user engagement can be associated with user loyalty levels. Bowden (2009) develops a theory of user engagement, which states that a company can improve its service or the product of a particular brand, thus ensuring customer loyalty. This can be seen in repeat purchases of a service or product. Many studies also argue that user engagement can affect user loyalty to a specific brand and company through the enhancement of product sales and effective advertising (Zheng et al., 2015). Third, user engagement relates to behavioral manifestation. Bijmolt et al. (2010) conceptualize user engagement as a behavioral manifestation comprising a number of related behavior interactions within communities. Van et al. (2010) consider user engagement as user behaviors toward a brand or a company.

Based on previous studies and delimitations (Van Doorn et al., 2010; Wu et al., 2018), we define user engagement in this paper as a behavioral manifestation of user interactions and involvement with health tasks in OHCs. Although the concept of user engagement is defined differently in various studies, most agree that the essence of user engagement lies in users' involvement and interactions with communities (Martínez-López et al., 2017). This is reflected in users' interest in the online community.

2.3. Social support theory

Social support refers to the exchange of information, emotions, knowledge, and resources between different people (Yan et al., 2015). There is a strong relationship between social support and health conditions. Social support enhances individuals' likelihood of insisting on treatments, changing their health behaviors, and improving their health conditions (McMullan, 2006). Hence, social support is one of the most important factors affecting individuals' health-related behaviors and health issues. In OHCs, social support relates to the exchange and delivery of information (i.e., knowledge and experience). The knowledge obtained through informational support helps users to better understand their own health problems, and this experience provides users with more opinions on the management of their health conditions (McMullan, 2006). Users can utilize this knowledge and experience to change their health-related behaviors and manage their own health (Bambina, 2007). Social support can be shown by the sharing of concern or happiness, or via messages sent between users. OHCs make it possible for users to interact with one another and obtain social support (Yan & Tan, 2014), regardless of the time or their location.

Support obtained through social support networks could assist individuals to cope with negative and stressful events (Balaji et al., 2016). Prior research has observed that individuals may receive social support from two features of social support networks: the network structure (such as its size) and its activities (Balaji et al., 2016; Maier et al., 2015). The network's structure may reflect the actual connection between individuals in the social support network (Thoits, 1995; Barrera, 1986), while activities relate to individuals' behaviors in the network (Barrera, 1986). These characteristics of social support networks might affect the amount of social support obtained by individuals through a social support network (Balaji et al., 2016). In this paper, the characteristics of social support networks are used as proxies for actual social support obtained by users from OHCs.

2.4. Gender difference theory

Extensive research has been conducted on the effects of gender differences in areas such as management, marketing, and psychology. In recent years, gender differences have been emphasized in studies on information systems and social media. For example, Sun et al. (2010) examine the role of gender differences in Web advertising evaluation, observing that gender differences moderate the relationship between advertising information, entertainment, and individuals' attitudes toward web advertising. Zhou et al. (2014) argue that gender differences moderate the relationships between user benefits and satisfaction in the virtual social world. Lin et al. (2017) investigate the moderating effects of users' gender differences on the relationships between related factors and social network continuance.

Generally, gender differences can be divided into three levels: the biological level, the cognitive level, and the social and behavioral level (Sun et al., 2010). First, the biological level of gender differences refers to the distinction in men's and women's biological structures on chromosomal and hormonal levels. As a consequence of men and women's biological differences, their cognitive and behavioral approaches are different.

Second, gender-based differences in cognitive levels arise as a consequence of differences in men's and women's information processing techniques and thinking processes (Gefen & Ridings, 2005). Men are known as selective processors—they focus and rely on high-value information and complicated messages (Sun et al., 2010). Conversely, women are known as comprehensive processors—they absorb all information without considering its value. Hence, men focus on important information and messages, while women consider the information and messages that they feel certain about.

Third, gender differences at the social and behavioral levels refer to individuals' behavioral motivations and to how men and women regard social relationships and identity (Campbell et al., 2001). Brackett et al. (2001) observe that at social and behavioral levels, men are independent and competitive; they care only about themselves and their dignity. Conversely, women are harmonious; they care about themselves and other people. Moreover, men and women have significantly different motivations (Sun et al., 2010). For example, men are motivated by goals and achievements; hence, they pay more attention to the performance of behaviors. Women, in contrast, are more concerned with maintaining harmonious relationships, and are motivated by affiliation.

3. Research model and hypothesis development

This paper examines the effects of social network structures and activities in OHCs. We also research the effects of user engagement in health tasks on the improvement of health conditions. Further, this paper examines the moderating effect of user gender on the relationship between social support networks, user engagement, and health conditions.

3.1. The effects of social support networks on user engagement

OHCs generally launch many health tasks to stimulate users to be more active. As a result of a lack of motivators, users can find engaging in online health tasks a stressful event. Hence, users need motivators to better engage in OHC tasks. Based on social support theory, social support is important for helping users to cope with negative and stressful events (Cohen & Wills, 1985). It is more likely for a user who has obtained social support in online communities to engage in and interact with OHCs, complete the health tasks, and change their health behaviors. Therefore, social support is vitally important if users are to engage in health tasks.

Users' social support networks in an OHC can influence the actual amount of support that they receive. In social support theory, two features of the social support network reflect online social support: the network's structure (such as its size) and its activities (Ba & Wang, 2013; Balaji et al., 2016). The network's size determines the amount of social support provided by the OHC, which may reflect the connection between individuals in the social support network. Generally, the greater the number of friends, the more social support an individual will receive (Ba & Wang, 2013; Yan & Tan, 2014). Large network size in OHCs increases the possibility of interaction between users, which is associated with increased levels of user engagement in health tasks. Therefore, as the social support network size increases, the level of user engagement in online health tasks also increases.

Further, activities in social networks are important for influencing levels of user engagement in health-related tasks. The activities that benefit from obtaining support can be divided into two aspects: individual activities and group member activities. Individual activities refer to a user's active behaviors in their social support network to obtain related support. Users who are active in interacting with other members in their social support networks and who frequently discuss related health issues tend to receive more support (Ba & Wang, 2013). They are also more likely to gather information and emotional support than inactive users. Therefore, individual user activities play an important role in helping users to obtain support through social support networks and engagement in online health tasks. Conversely, group member activities in social support networks are also crucial ways for users to procure support (Maier et al., 2015). Group member activities refer to the behaviors of other members in a user's social support network that provide support to that user. Group member activities make users feel that they are taken care of and are not isolated from society (Yan & Tan, 2014). Network member activities can also provide more health-related information and knowledge to assist users in changing their behaviors and engaging in online health tasks. Hence, both individual and group member activities are associated with increased levels of user engagement in online health tasks. Based on what has been discussed above, we hypothesize that:

H1. The size of a social support network is positively associated with the level of user engagement in online health tasks.

H2a. Individual user activities in social support networks are positively associated with the level of user engagement in online health tasks.

H2b. Group member activities in social support networks are positively associated with the level of user engagement in online health tasks.

Further, the size of social support networks and the activities they offer are each associated with increased levels of user engagement in online health tasks in complementary and substitutable ways. First, users in a large social support network have more opportunities to interact with other people because of the large number of online friends they have. If users actively interact with other users in a large social support network, they can obtain more support than users in small social support networks. The capacity of individual user activities will be strengthened as their social support network increases in size. In contrast, even if users actively interact with other people in a small social support network, they may obtain less support. The influence of individual user activities will weaken as their social support network decreases in size. Therefore, there is a complementary relationship between the size of social support networks and individual user activities.

Additionally, both the size of a social support network and its group member activities can reflect the companionship of members and the connection between individuals within the network. These two factors have a similar effect on users. For example, active member activities can provide support from group members, regardless of the size of the social network. The role of the social support network's size may be substituted for by group member activities. Conversely, even if other members are inactive, users still have access to a certain amount of social support from a large network. Hence, there is a substitutable relationship between the size of a social support network and its members' activities. Based on the discussion above, we hypothesize that:

H3a. The association of a social support network's size and its individual user activities with the level of user engagement in online health tasks is complementary.

H3b. The association of a social support network's size and its group member activities with the level of user engagement in online health tasks is substitutable.

3.2. The effects of user engagement on health conditions

Related studies on social support and health conditions observe that social support affects individuals' behavior and can improve their health conditions (Mccorkle et al., 2008). Therefore, users' health-related behaviors directly affect their health conditions. However, although individuals always try to manage their health conditions, the results are not always efficient. The main reason is that people lack scientific and appropriate health-management plans (Swift et al., 2014). Not only do irrational behaviors fail to improve health conditions, they can also produce worse outcomes. Health tasks launched by OHCs help users to implement a series of scientific health-management plans (e.g., exercise and dietary plans) that have been developed by fitness experts. In OHCs, users engage in and accomplish these health tasks to manage their own health conditions. User engagement in health tasks implements scientific health plans and changes users' health-related behavior, positively addressing their health conditions. Hence, improvement in health conditions could result from user engagement in health tasks. Based on what has been discussed above, we hypothesize that:

H4. The level of user engagement in online health tasks is positively associated with improvements in user health conditions.

3.3. The moderating effects of gender difference

Gender differences relate to individuals' behavioral and social orientations (Gefen & Straub, 1997). With regard to social orientation, gender difference theory posits that men are more independent and concerned with themselves (Sun et al., 2010), while women tend to pursue harmonious relationships. Hence, women care not only about themselves, but also for others. With regard to behavioral orientation, men's and women's behaviors are influenced by different motivations (Hoffman, 1972; Mcclelland, 1975). Generally, men are motivated by achievements, while women are motivated by affiliation. In other words, men are more performance-oriented, while women are driven by the harmony of relationships.

In OHCs, men and women react differently to the size of and to the activities offered by social support networks. Individual user activities and group member activities are user behaviors for obtaining social support in a social support network. Individual user activities and group member activities in social support networks can help users interact with other users and receive more information and emotional support. As men are more independent and assertive (Sun et al., 2010), they tend to adhere to their own ideas and interact less with others. In contrast, women are more relationship-oriented and tend to interact more with other users to establish harmonious relationships and obtain social support (Zhou et al., 2014). Hence, women value individual and group member activities in social support networks more than men do. When users engage in online health tasks via social support networks, the effects of these activities are fewer for men than for women.

The size of social support networks can be regarded as an achievement of social interaction, reflecting an individual's online status and embeddedness in a social network (Ellison et al., 2014). According to gender difference theory, men are motivated by achievements and are more concerned with their social statuses and achievements than women (Sun et al., 2010). To preserve their social status and sense of achievement, men tend to pay attention to the size of social support networks because the number of friends and followers reflects an individual's status and achievement. Moreover, as this theory suggests, men are competitive (Brackett & Carr, 2001). Social support networks provide the opportunity to compete with other members and display accomplishments. The larger the social network size, the greater the chance users have to show off their achievements. Thus, the size of social support networks, when it comes to engaging in online health tasks, has a greater effect for men than for women.

In addition, gender difference theory claims that men pay more attention to the results and the performance of things than women (Hoffman, 1972; Mcclelland, 1975). This means that when men and women undertake the same task, men expect better results than women. Women make judgments based on sensibility and are less sensitive to performance than men. When facing online health tasks in OHCs, women are more likely to enjoy the process of performing these tasks and men are more likely to be concerned with the results of the tasks. Therefore, user engagement in health tasks affects the health conditions of male users more strongly than it does those of female users. Based on what has been discussed above, we hypothesize that:

H5. The association between the size of the social support network and the level of engagement in health tasks is stronger for male users than for female ones.

H6a. The association between individual activities in social support networks and levels of engagement in health tasks is stronger for female users than male ones.

H6b. The association between group member activities in social support networks and levels of engagement in health tasks is stronger for female users than male ones.

H7. The association between levels of engagement in health tasks and health conditions is stronger for male users than female ones.

Figure 1 depicts our research model.

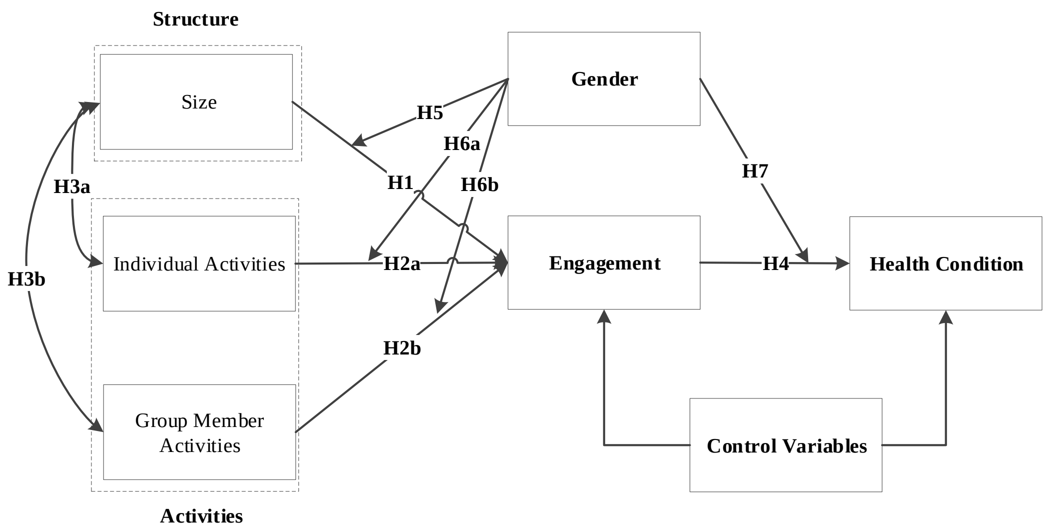

Figure 1: Research model

4. Research method

4.1. Data collection and measures

To test the hypotheses of our research model, data from the website bohe.com—the largest online weight-loss community in China—were collected. Users in this OHC upload their data to manage their health conditions and body weight. The data include users' age, gender, height, initial body weight, and current body weight. This digital community not only assists users in caring for themselves, but also provides a social interaction interface. Users can use this website to exchange information, obtain social support, and develop friendships. The selected OHC offers sufficient information for the empirical research of this paper since a high volume of data and information can easily be gleaned from it.

A software program was created to download the website's content automatically. To protect user privacy, the webpage of this OHC does not directly present user demographic information, such as gender and age. However, it provides an option for users to find friends online by filtering people based on their demographic information. This option has been used for the collection of our research data. For example, we can search by users' demographic information (e.g., male users, aged 20 to 24). To ensure validity, this paper mainly collected information about highly active users. In addition, this paper used a JAVA program to add information and data to an established database. After removing invalid data, the data of 1,129 users were collected. Table 2 shows the demographic information of our data.

Table 2: Demographic information (1,129 users)

	Frequency	Percentage
Gender		
Female	530	46.9%
Male	599	53.1%
Age		
20–24	334	29.6%
25–29	378	33.5%
30–34	417	36.9%

This paper used a two-equation model to test all research hypotheses. Therefore, there were two dependent variables in our research model. With the first equation, we investigated the influences of social support networks on the levels of user engagement in health tasks, and the dependent variable in this equation was the level of user engagement. In our research, there was an important index (i.e., the number of awards) reflecting the level of user engagement in health tasks. These awards were given to users who had accomplished the health tasks launched by the OHCs. The greater the number of awards a user received, the higher the level of user engagement in the health tasks and vice versa. Hence, the number of awards formed a proxy for the level of user engagement in health tasks.

In the second equation, this paper examined the effect of engagement on users' health conditions. The method that was adopted to measure improvements in health conditions was the users' weight-loss performance (initial body weight minus current body weight) in the OHC. The unit for this variable was the kilogram.

The independent variables included the three characteristics of social support networks: network size, individual user activities, and group member activities. First, the number of friends that a user had in an OHC was used as a proxy for the size of the social support network. Users typically received and provided social support to one another as online friends. The more online friends users had, the more social support they would receive or give. Hence, the number of friends in an OHC could reflect the size of the social support network. Second, we took the number of posts that users shared in an OHC as a proxy for their individual activities. In our research, a user could publish a post about health-management information, an individual health condition, or a health plan to interact with other users. Therefore, the number of posts could effectively reflect the efforts of individuals to obtain social support. Third, this paper used the number of visits that a user's homepage had as a proxy for group member activities. The number of visits to users' homepages reflected the users' activities as they sent messages to other members whom they cared about. Hence, the number of visits formed an effective proxy for group member activities in the social support network. The moderating variable in our research model was user gender. In this paper, we used a dummy variable to represent gender differences. Women and men were expressed as 0 and 1 respectively.

In addition, we controlled user age as a demographic variable in the research model. We also considered the number of days since each user's registration to control for usage time. Further, this study controlled for differences in obesity levels throughout the OHC. The Body Mass Index (BMI) was used to measure the degree of user obesity, as this could affect user behavior and health conditions. The World Health Organization states that a BMI in the range of 18.5 to 24.9 is ideal, while a BMI value of greater than 24.9 means that an individual is overweight, and a BMI value of lower than 18.5 indicates that an individual is underweight. Hence, the BMI is an effective measure for users' levels of obesity. We used initial body weight to calculate users' BMI and to ascertain their initial body conditions. The specific method used to calculate BMI was as follows:

$$\mathbf{BMI = Weight\ (kg)/Height^2\ (m)}$$

Table 3 shows the variable descriptions. Tables 4 and 5 present the descriptive statistics and the correlations of independent and dependent variables in the research model respectively.

Table 3: Description of variables

Variable Type	Variable Name	Measurement
Dependent variable	Engagement	The number of awards as a proxy for the level of user engagement in health tasks
	Health condition	Using weight loss as proxy for users' health conditions
Independent variable	Group member activities	The number of visitors to a member's page
	Individual activities	The number of posts
	Size	The number of online friends each user has
Moderating variable	Gender	Male = 1, Female = 0
Control variable	Age	User age
	BMI	BMI = Weight (kg)/Height^2 (m)
	Usage time	The number of days since users joined the OHC

Table 4: Descriptive statistics of variables (N = 1,129)

	Min	Max	Mean	Deviation
Age	20.000	34.000	27.573	2.454
Gender	0.000	1.000	0.530	0.499
Usage time	3.000	271.000	138.330	51.684
Size	0.000	2,418.000	15.791	90.619
Individual activities	0.000	9,107.000	37.669	344.906
Group member activities	0.000	94,126.000	1,038.884	3,565.937
BMI	19.010	39.200	28.258	4.799
Engagement in health tasks	100.000	42,162.000	599.750	2029.356
Health condition	1.000	37.000	17.049	12.053

Table 5: Correlations of variables (N = 1,129)

Variables	1	2	3	4	5	6	7	8	9
1 Age	1								
2 Gender	0.014	1							
3 Usage time	−0.180	0.243**	1						
4 Members	0.074*	−0.093**	0.013	1					
5 Size	0.053	−0.145**	0.013	0.279**	1				
6 Individuals	0.065*	−0.091**	0.055	0.434**	0.534**	1			
7 BMI	0.113**	0.177**	0.062*	−0.047	−0.003	−0.012	1		
8 Engagement	0.110**	−0.181**	0.038	0.609**	0.568**	0.659**	−0.041	1	
9 Health	0.157**	−0.122**	0.044	−0.005	0.036	0.017	0.577**	0.039	1

** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

4.2. Model estimation

In this paper, we established a two-equation model to test our hypotheses. In the first equation, we investigated the effects of social support networks on the levels of user engagement in health tasks. In the second equation, we examined the influence of user engagement in health tasks. Since the distribution of the dependent variables was not normal, we developed the following log-linear regression model. The two-equation model is as follows:

Equation 1:

$$Log(Engagement_i) = a_0 + a_1Age_i + a_2Gender_i + a_3log(Day_i) + a_4BMI_i + a_5Log(Size_i) + a_6Log(Individuals_i) + a_7 Log(Members_i) + a_8Gender_i * Log(Size_i) + a_9 Gender_i * Log(Self_i) + a_{10}Gender_i * Log(Members_i)+u_i$$

Equation 2:

$$Log(HealthCondition_i) = b_0+b_1Age_i + b_2Gender_i + b_3log(Day_i) + b_4BMI_i + b_5Log(Engagement_i) + b_6Gender_i * Log(Engagement_i) + \varepsilon_i$$

Let i = 1 … N index the user. Here, a_0 to a_{10} are the parameters to be estimated in the first equation. The variables Gender * log(Individuals), Gender * Log(Individuals) and Gender * Log(Members) are interactive terms to test the moderating effects of gender differences. The term μ_i is an error term in the first equation. b_0 to b_6 are the parameters to be estimated in the second equation, and ε_i is an error term associated with observation i.

4.3. Empirical analysis and results

Table 6 shows the estimated result of the first equation and presents the empirical models hierarchically. We show the model with the control variables only in Column 1 and add the independent variables and interaction terms in Columns 2, 3, 4, and 5 respectively. Table 7 shows the estimated result of the second equation hierarchically. We show the model with the control variables only in Column 1, and add the independent variables and interaction terms in Columns 2 and 3 respectively. In the first and second equations, the adjusted R square and F values of the regressions are reasonable and statistically significant.[2] The mean variance inflation factor statistics of the variables are less than 2.0, indicating that there is no significant multicollinearity among the independent variables.

[2] The reason why R^2 in Columns 2 and 3 of Table 6 becomes lower is that interaction terms lead to a decrease in the linearity of the first equation.

Table 6: Parameter estimates of the first equation

Independent Variable	1 Control	2 Main	3 Moderator	4 Interaction	5 All
Constant	2.796***	4.077***	4.094***	4.059***	4.083***
	(7.507)	(19.722)	(19.249)	(19.900)	(19.253)
Age	0.122***	0.033***	0.030***	0.035***	0.033***
	(11.752)	(5.430)	(4.992)	(5.904)	(5.509)
Gender	−0.950***	−0.182***	−0.011	−0.187***	−0.064
	(−17.344)	(5.361)	(−0.143)	(−5.515)	(−0.789)
Log(day)	0.087**	0.002	−0.003	0.013	0.008
	(2.389)	(0.075)	(−0.162)	(0.644)	(0.391)
BMI	−0.001	−0.011***	−0.011***	−0.012***	−0.011
	(−0.256)	(−3.748)	(−3.605)	(−3.934)	(−3.837)
Log(size)		0.284***	0.237***	0.250***	0.210***
		(15.629)	(10.406)	(9.921)	(7.055)
Log(individuals)		0.099***	0.139***	−0.012	0.010
		(5.217)	(5.986)	(−0.447)	(0.302)
Log(members)		0.205***	0.217***	0.224***	0.242***
		(21.134)	(17.127)	(16.691)	(13.558)
Gender * Log(size)			0.122***		0.107***
			(3.352)		(2.946)
Gender * Log(individuals)			−0.111***		−0.053**
			(−2.778)		(−2.008)
Gender * Log(members)			−0.030		−0.040
			(−1.541)		(−1.297)
Log(size) * Log(individuals)				0.040***	0.040***
				(5.794)	(5.606)
Log(size) * Log(members)				−0.013**	−0.013**
				(−2.427)	(−2.325)
Adjust-R Square	0.286	0.785	0.707	0.791	0.794
F	114.036***	588.691***	416.702***	474.683***	359.104***
N	1,129	1,129	1,129	1,129	1,129

t statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01

Table 7: Parameter estimates of the second equation

Independent variable	1 Control	2 Main	3 All
Constant	−38.284***	−41.796***	−34.104***
	(−9.265)	(−9.930)	(−7.485)
Age	0.475***	0.321***	0.215*
	(4.107)	(2.636)	(1.745)
Gender	−5.924***	−4.731***	−20.205***
	(−9.751)	(−6.959)	(−5.430)
Log(day)	0.703	0.593	0.596
	(1.732)	(1.467)	(1.484)
BMI	1.521***	1.523***	1.512
	(25.555)	(25.737)	(25.727)
Log(Engagement)		1.256***	0.427
		(3.818)	(1.122)
Gender * Log(Engagement)			2.845***
			(4.229)
Adjust-R Square	0.392	0.399	0.408
F	182.979***	151.068***	130.763***
N	1,129	1,129	1,129

t statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01

Hypothesis 1 predicts that the size of a social support network is positively associated with the level of user engagement in health tasks. According to Column 2 of Table 6, Hypothesis 1 is supported by our empirical results. The coefficient of the size of a social support network ($a = 0.284$, $t = 15.629$, $p < 0.01$) is positive and statistically significant. The results show that a growth in the size of a social support network leads to higher levels of user engagement in health tasks. Hence, the size of social support networks is positively associated with the level of user engagement in health tasks.

Hypothesis 2a posits that individual user activities in a social support network are positively associated with the level of user engagement in health tasks. According to Column 2 of Table 6, the coefficient of individual user activities ($a = 0.099$, $t = 5.217$, $p < 0.01$) is positive and statistically significant. This result supports our Hypothesis 2a. Individual user activities in a social support network can promote levels of engagement in health tasks. Further, Hypothesis 2b states that other members' activities in the social support network are positively associated with levels of user engagement in health tasks. Column 2 of Table 6 provides support for this hypothesis because the coefficient of members' activities ($a = 0.205$, $t = 21.134$, $p < 0.01$) is positive and statistically significant. Therefore, other members' activities can provide users with support to promote their levels of engagement in health tasks.

Hypothesis 3a predicts that the association of a social support network's size and individual user activities with the level of user engagement is complementary. According to Column 4 of Table 6, the coefficient of the interaction term (size* individuals, $a = 0.040$, $t = 5.794$, $p < 0.01$) is positive and statistically significant. This result supports our Hypothesis 3a. Further, Hypothesis 3b posits that the association of a social support network's size and its members' activities with levels of user engagement in online health tasks is substitutable. According to Column 4 of Table 6, the coefficient of the interactive term (size* members, $a = -0.013$, $t = -2.427$, $p < 0.05$) is negative and statistically significant, indicating that Hypothesis 3b is supported.

Hypothesis 4 predicts that the level of user engagement in health tasks is positively associated with users' health conditions. According to Column 2 of Table 7, the coefficient of user engagement in health tasks ($b = 1.256$, $t = 3.818$, $p < 0.01$) is positive and statistically significant. This result supports our Hypothesis 4 and indicates that when the level of user engagement in health tasks improves, users' health conditions will also improve.

In addition, Hypotheses 5, 6a, 6b, and 7 predict the moderating effects of gender differences on the relationship between social support networks, user engagement, and users' health conditions. According to Column 3 of Table 6, the coefficient of the interactive terms Gender * log(size) ($a = 0.122$, $t = 3.352$, $p < 0.01$) and Gender * Log(individuals) ($a = -0.111$, $t = -2.778$, $p < 0.01$) are positive and statistically significant, indicating that gender differences moderate the effects of the size of social networks, as well as those of individual user activities, on levels of user engagement in health tasks. However, there is no evidence that supports Hypothesis 6b because the coefficient of the interactive term Gender * Log(members) ($a = -0.030$, $t = -1.541$, $p > 0.1$) in Column 3 of Table 6 is not statistically significant. Nonetheless, Column 3 of Table 7 provides support to Hypothesis 7 because the coefficient of the interactive term ($b = 2.845$, $t = 4.229$, $p < 0.01$) is positive and statistically significant. Figures 2, 3, and 4 show the moderating effects of gender differences.

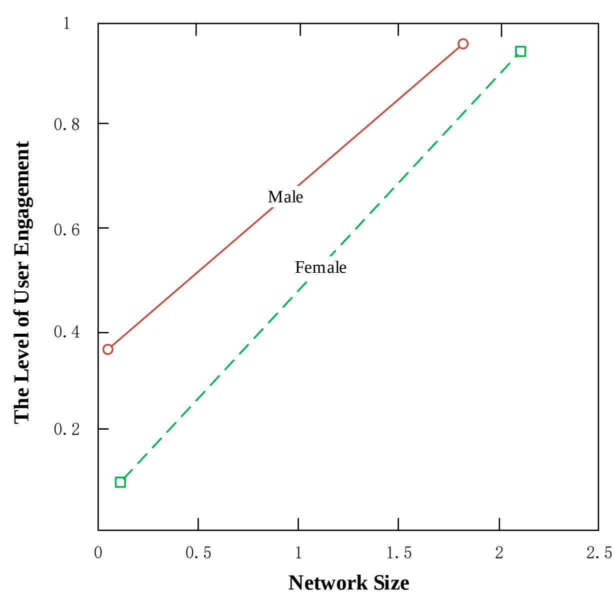

Figure 2: The moderating effects of gender difference on H4

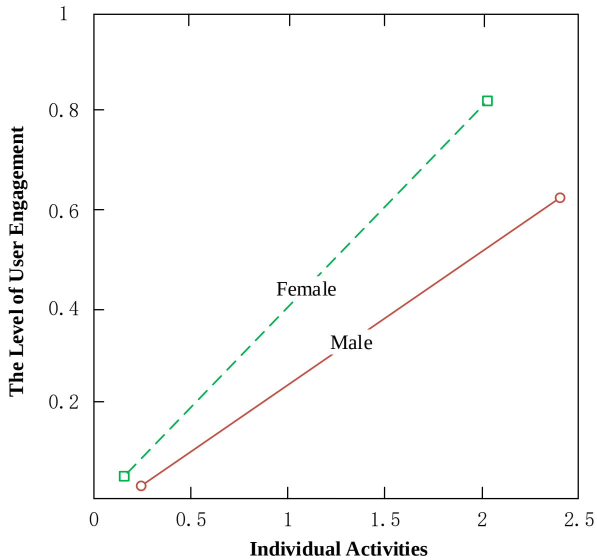

Figure 3: The moderating effects of gender difference on H6a

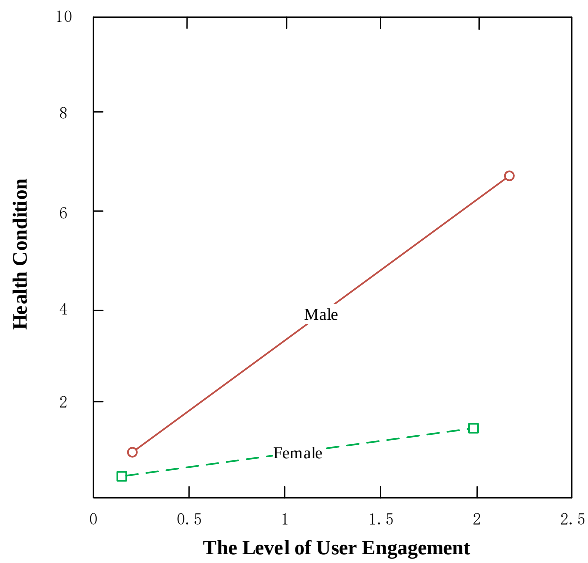

Figure 4: The moderating effects of gender difference on H7

4.4. Robustness checks

To examine the robustness of the moderating effects of gender differences in our research model, we divided all of our data into two subsamples based on user gender and re-ran the models in the two subgroups. We then compared the coefficients of the independent variables in the first and second equations for the male and female data to verify the moderating effects of gender differences.

Table 8 shows the estimated results of the first equation for the male and female subgroups. Network size, individual user activities and group member activities in social support networks are all positive and statistically significant in the male and female groups. Further, the coefficient of network size in the male group (0.346) is larger than that of the female group (0.245), and the coefficient of individual user activities in the male group (0.041) is smaller than that of the female group (0.134). The coefficients of group member activities in the male and female groups do not have significant differences (0.184 and 0.216).

Table 9 shows the estimated results of the second equation for the male and female subgroups. The level of user engagement is positive and statistically significant in the male and female groups, and the coefficient in the male group (3.299) is larger than that of the female group (0.431). Hence, the results of the robustness checks are consistent with the results of the main model.

Table 8: Robustness checks of the first equation

Independent Variable	Male	Female
Constant	4.232***	4.404***
	(11.95)	(13.193)
Age	0.036***	0.024**
	(5.438)	(2.340)
BMI	−0.006**	−0.019***
	(−1.960)	(−3.238)
Log(day)	−0.065	0.004
	(−1.414)	(0.138)
Log(size)	0.346***	0.245***
	(15.032)	(8.850)
Log(individuals)	0.041***	0.134***
	(15.98)	(4.762)
Log(members)	0.184*	0.216***
	(1.941)	(14.096)
Adjust-R Square	0.742	0.731
F	288.037***	240.129***
N	599	530

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Robustness checks of the second equation

Independent Variable	Male	Female
Constant	−52.525***	−35.946***
	(−5.085)	(−7.642)
Age	0.213	0.215
	(1.071)	(1.494)
BMI	1.473***	1.574***
	(17.359)	(20.013)
Log(day)	0.489	0.615*
	(0.385)	(1.711)
Log(engagement)	3.299***	0.431*
	(4.760)	(1.841)
Adjust-R Square	0.378	0.442
F	91.934***	103.850***
N	599	530

t statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.5. Post-hoc analysis

Although our results have shown that social support networks are positively associated with levels of engagement in health tasks, there could be potential issues surrounding the self-selection of users and the endogeneity of variables in our research model. To reduce such issues, this paper uses a method that combines propensity score matching and difference-in-difference analysis to build a quasi-experiment. Propensity score matching that creates a statistical balance can assist in reducing user self-selection and difference-in-difference analysis can reduce the endogeneity of variables.

Our research data show that many users have no online friends, never interact with other people, and have few visitors. This generated a natural research context for our quasi-experiment. We divided users' data into two periods: the initial period and the current period. The initial period refers to the period when users had just commenced using the OHC. In this period, all users' social support networks and levels of engagement were set to zero. The current period refers to the period when the data were collected. We used a dummy variable to express the initial and current periods as 0 and 1 respectively. According to the value of the independent variables, if a user had online friends, we would mark them as 1 and if a user had no online friends, we would express it using 0. Similarly, we also expressed the presence of posts on a user's page, or their absence, using 0 and 1 respectively. However, only a few users had no visitors; therefore, we recognized users with fewer than ten visitors as 0 and users with more than ten visitors as 1. Subsequently, we gathered the personal information of users (e.g., age, gender, BMI and usage time) to calculate the propensity score, before using these scores to locate matched pairs. Table 10 displays the results of the propensity score matching. Finally, we used difference-in-difference analysis to explore the influence of social support network size, individual activities, and group member activities on levels of engagement. Table 11 shows the results of the difference-in-difference analysis. Figure 5 shows the research process of the post-hoc analysis.

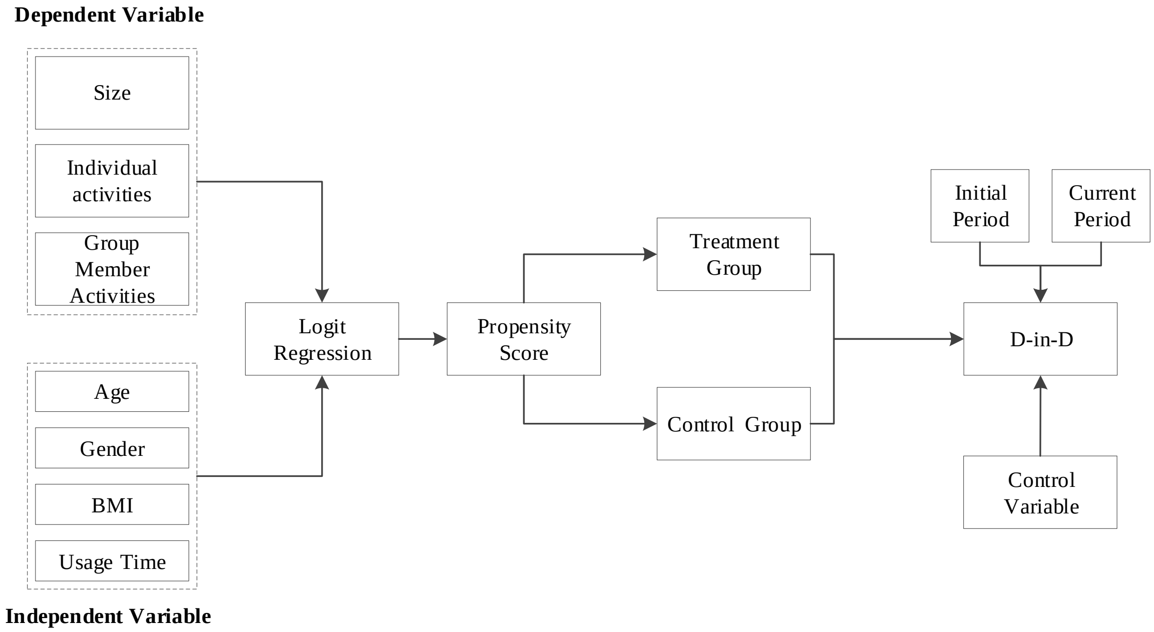

Figure 5: The results of the difference-in-difference analysis

Table 10: The results of the propensity score matching

Match type	Size	Individual user activities	Group member activities
Fuzzy matches	276	108	329
Unmatched including missing keys	297	913	375
Unmatched with valid keys	297	913	375
Sampling	Without replacement	Without replacement	Without replacement
Log file	None	None	None
Maximize matching performance	Yes	Yes	Yes

Table 11: The results of the difference-in-difference analysis

Variable	Size	Individuals	Members
constants	−0.502	−0.608	−0.872***
	(−1.608)	(3.316)	(−3.295)
age	0.032***	0.034***	0.043***
	(3.756)	(2.894)	(−0.312)
gender	−0.221***	−0.316***	−0.353***
	(−4.502)	(−4.887)	(−9.416)
Log(day)	0.011	−0.012	0.045
	(0.423)	(−0.253)	(1.459)
BMI	−0.007**	0.001	−0.006**
	(−2.016)	(0.241)	(−2.073)
time	5.243***	5.441***	5.077***
	(151.465)	(87.187)	(162.982)
treated	−0.008***	−0.004	−0.011
	(−0.845)	(−0.215)	(−0.798)
time* treated	0.732***	0.390***	0.617***
	(11.115)	(3.637)	(10.818)
N	552	216	642
F	5,592.15	1,795.76	6,507.64
R^2	0.963	0.963	0.964

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

According to Columns 1, 2, and 3 of Table 9, the results of the post-hoc analysis show that the size of a social support network, the individual user activities, and the group member activities positively affect the levels of user engagement in health tasks because all the coefficients of the interactive term (time*treated) are positive and statistically significant. These results are consistent with the results of the main model. This analysis mitigates concerns about self-selection and the endogeneity of the research model.

5. Discussion and implication

5.1. Discussion

In this paper, we investigated the influence of social support networks, in terms of their structures and activities, on levels of user engagement in health tasks. Following social support theory, this paper hypothesized in Hypotheses 1, 2a, and 2b that, in OHCs, the size of a social network, the individual user activities, and the group member activities are positively associated with levels of user engagement in health tasks. The results of our empirical research support these hypotheses. First, the size of a social support network reflects the actual connection between users in OHCs. The greater the social support network, the more social support users will receive. Second, individual user activities and group member activities reflect the active and passive deliveries of related support within OHCs respectively, thus affecting levels of user engagement in health tasks. Therefore, the size of a social network, individual user activities, and group member activities are all crucial for users to obtain greater support, thus enhancing levels of user engagement in health tasks. Eventually, these factors will also influence users' health-related behaviors.

Moreover, we found the relationship between social support network size and activities to be associated with levels of user engagement in health tasks. In Hypotheses 3a and 3b, we posited that the association of a social support network's size and its individual user activities with levels of user engagement was complementary, and that the effect of a social support network's size and its group member activities on levels of user engagement is substitutable. The results of our research support these two hypotheses. Individual user activities will either strengthen or weaken with the increasing or decreasing of their social support network size. Thus, there is a complementary relationship between the size of a social support network and its individual user activities. Additionally, the function of the social support network's size may be substituted by its group member activities.

Another finding of our research was the effect of user engagement in health tasks on the improvement of health conditions. In Hypothesis 4, we posited that the level of user engagement in health tasks is positively associated with an improvement in users' health conditions. Our empirical research provides evidence to support Hypothesis 4. Users' health-related behaviors can be inferred from the levels of their engagement in health tasks. Users obtaining support through social support networks may be more likely to engage with OHCs to exercise and complete health tasks, hence changing their health-related behaviors and enhancing their health conditions. Therefore, users' social support networks are the antecedent to engaging in health tasks, while improvements in health conditions are the result of users' engagement in health tasks.

We also examined the moderating effect of gender differences in OHCs. In Hypotheses 5, 6a, 6b, and 7, we posited that gender differences moderate the relationship between social support networks, user engagement, and user health conditions. The results of our empirical research show that the size of a social support network has a greater effect on male users than on female ones, while individual user activities as part of health tasks have a stronger effect on female users than on male ones. Hypotheses 5 and 6a are supported by our empirical model. Women are relationship-oriented. They tend to interact with other users and accept other users' opinions to maintain strong relationships with other users. Conversely, men are more concerned with their social statuses than women, leading them to pay more attention to the size of their social support networks, as the number of friends and followers reflects an individual's social status. However, we did not find evidence to support Hypothesis 6b, which suggests that group member activities in social support networks have a stronger effect on female users than on male ones. One possible explanation for this is that the variable used to measure group member activities in social support networks (i.e., the number of visits to a user's homepage) did not reflect the exchanges of social support and members' opinions. In gender difference theory, women tend to accept other people's opinions and men tend to neglect the suggestions of others. Although the number of visits to a user's homepage may reflect other members' levels of concern, it is not able to indicate the content of informational and emotional support. Hence, the number of visits to a user's homepage does not show significantly different effects for women and men.

The results of the research model suggest that user engagement in health tasks has a stronger influence on male users than on female ones. Hypothesis 7 is supported by our research results. As men are more concerned with the performance of tasks than women, user engagement has a greater effect on male users' health conditions than on those of female users. Hence, gender differences moderate the relationship between social support networks, user engagement, and user health conditions.

5.2. Theoretical implications

The main contributions of our research can be summarized in the following points. First, this paper offers a systematic way of investigating the role of social support networks in OHCs in terms of the structure of the social support network and the activities of its users. Although previous research has already examined the effects of social support (informational and emotional support), not many studies have concentrated on the effects of social support networks on user engagement where both the structure of social networks and the activities of their users in OHCs are investigated together. Hypotheses were developed to investigate the effects of network size, individual user activities, and group member activities on levels of user engagement in health tasks. These hypotheses were empirically tested and supported. Our empirical results contribute to social support theory and the existing research by providing a greater understanding of the role of social support networks in OHCs.

Second, despite the prevalent use of social support networks, whether there are potential interactions between the size of the social support networks, individual user activities, and group member activities remains unknown, especially in the context of OHCs. This paper found that the association of social support network size and individual user activities with levels of user engagement is complementary, and, further, that the effects of social support network size and group member activities on levels of user engagement are substitutable. This finding assists us in understanding the relationship between social support network size and activities in OHCs.

Third, we investigated the antecedents and results of user engagement in health tasks. Although extensive studies have examined the role of user engagement in online brand communities, research that systematically investigates the role of user engagement in OHCs is limited. To address this research gap, we studied the antecedents and results of user engagement in health tasks simultaneously. Our empirical results reveal that the structures of social support networks and the activities within social support networks affect the level of user engagement in health tasks. Further, levels of user engagement in health tasks are positively associated with the improvement of user health conditions. This finding forms an extension of related research on user engagement in online communities.

Fourth, in this paper, we investigate the moderating effects of gender differences on the relationship between social support networks, user engagement, and health conditions. To our knowledge, there have been limited studies on the moderating effects of user characteristics on the relationship between influencing factors and users' health conditions in OHCs. To address this research gap, this paper builds an empirical model to study the moderating effects of gender differences in OHCs. Our empirical results demonstrate that gender differences change the affecting mechanisms of social support networks and user engagement in health tasks. This finding helps us to understand the roles of user gender differences in OHCs and expands gender difference theory into research on OHCs.

5.3. Implications for practice

This paper has provided insights into the management of health conditions as well as the design of OHCs for users and practitioners. First, the results of this paper suggest that the network size and activities of a social support network influence the levels of user engagement in health tasks, subsequently improving users' health conditions. The designers of OHCs should further develop the mechanisms of social support networks to influence the level of user engagement in terms of user interaction with OHCs, as well as involvement in health tasks, and assistance with managing health conditions. Besides considering enhancement through individual user activities in social support networks, designers could also stimulate other group members' activities. For example, designers of OHCs can stimulate users to publish posts that can increase interaction with other people and encourage users to visit each other's homepages. Additionally, designers could create new tasks and activities that provide ranking and monetary rewards for users to encourage them to interact with other individuals, to make more online friends and to expand their network sizes.

Second, this paper has revealed the moderating effects of gender differences. Men pay more attention to the size of their social support networks and their performance than women. Conversely, women are more relationship-oriented and tend to interact with other users and accept their opinions to maintain strong relationships with them. Perhaps the designers of OHCs could design different sets of incentive-based mechanisms for men and women to help them to better manage their health conditions. For example, for male users, designers could focus on offering greater rewards upon the completion of health tasks to encourage male users to complete more exercises, since these users pay more attention to their performance. For female users, such a mechanism of social interaction should be designed to improve levels of engagement, because women are more receptive to the opinions of others.

5.4. Limitations and future research

There are several limitations to this paper. First, the research was conducted using a specific OHC to test the effects of social networks and user engagement on users' health conditions in this community. In future, data could be collected from several different OHCs. Second, only network size, individual user activities, and group member activities were used to examine the effects of social support networks on OHCs. In subsequent research, more variables could be added to reflect the roles of social support networks in OHCs. Third, only cross-sectional data were used to perform regression analysis. This method limits the identification of relationships between network size, activities, user engagement, and users' health conditions. In contrast, an empirical model based on panel data could be used in the future to validate the results.

6. Conclusion

Extensive studies have been conducted on OHCs to investigate the effects of social support on users' health conditions. However, past research has overlooked the role of social support networks and user engagement. Moreover, there are limited studies examining the moderating effects of gender differences on the relationship between social support networks, user engagement, and users' health conditions. To address these research gaps, an empirical model based on social support theory and gender differences was established in this paper. It aimed to examine the effects of social support networks, user engagement, and gender differences on users' health conditions. Based on the data collected from an OHC in China, the empirical results of this research model revealed that network size, individual user activities, and group member activities are positively correlated with levels of user engagement in health tasks, as well as with the relationship between these three factors. Moreover, levels of user engagement in health tasks are positively related to improvements in users' health conditions. In addition, our results show the moderating effects of gender differences on the relationship between social support networks, user engagement, and users' health conditions. These findings contribute to the literature on OHCs and provide users and practitioners with a new perspective.

Acknowledgment

This study was partially funded by the China Postdoctoral Science Foundation Grant (2017M622647) and the National Natural Science Foundation of China Grant (71572050; 71771065; 71490724). The authors greatly appreciate the work of the editors and anonymous reviewers and are grateful for their insightful comments and suggestions. All errors remain ours.

REFERENCES

Ba, S. and Wang, L., "Digital health communities: The effect of their motivation mechanisms," Decision Support Systems, Vol. 55, No. 4:941-947, 2013.

Balaji, M. S., Khong, K. W. and Chong, A. Y. L., "Determinants of negative word-of-mouth communication using social networking sites," Information & Management, Vol. 53, No. 4:528-540, 2016.

Baldus, B. J., Voorhees, C. and Calantone, R., "Online brand community engagement: Scale development and validation," Journal of Business Research, Vol. 68, No. 5:978-985, 2015.

Ballantine, P. W. and Stephenson, R. J., "Help me, I'm fat! Social support in online weight loss networks," Journal of Consumer Behaviour, Vol. 10, No. 6:332-337, 2011.

Bambina, A., Online social support: the interplay of social networks and computer-mediated communication, NY, Cambria Press, 2007.

Bansal, G., Zahedi, F. and Gefen, D., "The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online," Decision Support Systems, Vol. 49, No. 2:138-150, 2010.

Bijmolt, T. H. A., Leeflang, P. S. H., Block, F., Eisenbeiss, M., Hardie, B. G. S., Lemmens, A. and Saffert, P., "Analytics for Customer Engagement," Journal of Service Research, Vol. 13, No. 3:341-356, 2010.

Bowden, J. L.-H., "The Process of Customer Engagement: A Conceptual Framework," Journal of Marketing Theory & Practice, Vol. 17, No. 1:63-74, 2009.

Brackett, L. K. and Carr, B. N., "Cyberspace advertising vs. other media: Consumer vs. mature student attitudes," Journal of Advertising Research, Vol. 41, No. 5:23-32, 2001.

Brodie, R. J., Ilic, A., Juric, B. and Hollebeek, L., "Consumer engagement in a virtual brand community: An exploratory analysis," Journal of Business Research, Vol. 66, No. 1:105-114, 2013.

Campbell, P. G., Macauley, D., Mccrum, E. and Evans, A., "Age differences in the motivating factors for exercise," Journal of Sport & Exercise Psychology, Vol. 23, No. 3:191-199, 2001.

Cohen, S. and Wills, T. A., "Stress, social support, and the buffering hypothesis," Psychological Bulletin, Vol. 98, No. 2:310-357, 1985.

Ellison, N. B., Vitak, J., Gray, R. and Lampe, C., "Cultivating social resources on social network sites: Facebook relationship maintenance behaviors and their role in social capital processes," Journal of Computer-Mediated Communication, Vol. 19, No. 4:855–870, 2014.

Fox, N. J., Ward, K. J. and O'rourke, A. J., "The 'expert patient': empowerment or medical dominance? The case of weight loss, pharmaceutical drugs and the Internet," Social Science & Medicine, Vol. 60, No. 6:1299-1309, 2005.

Gefen, D. and Ridings, C. M., "If you spoke as she does, sir, instead of the way you do:a sociolinguistics perspective of gender differences in virtual communities," Acm Sigmis Database, Vol. 36, No. 2:78-92, 2005.

Gefen, D. and Straub, D. W., Gender differences in the perception and use of E-mail: an extension to the technology acceptance model, Society for Information Management and The Management Information Systems Research Center, 1997.
Hoffman, L. W., "Early Childhood Experiences and Women's Achievement Motives," Journal of Social Issues, Vol. 28, No. 2:129-155, 1972.
Hwang, K. O., Ottenbacher, A. J., Green, A. P., Cannon-Diehl, M. R., Richardson, O., Bernstam, E. V. and Thomas, E. J., "Social support in an Internet weight loss community," International journal of medical informatics, Vol. 79, No. 1:5-13, 2010.
Li, H., Lai, V. S. and Luo, X., "Understanding the role of social situations on continuance participation intention online communities: an empirical perspective," Journal of Electronic Commerce Research, Vol. 17, No. 4: 358-380, 2016.
Lin, X., Featherman, M. and Sarker, S., "Understanding factors affecting users social networking site continuance," Information & Management, Vol. 54, No. 3:383-395, 2017.
Liu, X., Guo, X., Wu, H. and Wu, T., "The impact of individual and organizational reputation on physicians' appointments online," International Journal of Electronic Commerce, Vol. 20, No. 4:551-577, 2016.
Maier, C., Laumer, S., Eckhardt, A. and Weitzel, T., "Giving too much social support: social overload on social networking sites," European Journal of Information Systems, Vol. 24, No. 5:447-464, 2015.
Manuel, B., "Distinctions between social support concepts, measures, and models," American Journal of Community Psychology, Vol. 14, No. 4:413-445, 1986.
Martínez-López, F. J., Anaya-Sánchez, R., Molinillo, S., Aguilar-Illescas, R. and Esteban-Millat, I., "Consumer engagement in an online brand community," Electronic Commerce Research & Applications, Vol. 23:24-37, 2017.
Mcclelland, D. C., "Power: The inner experience," Oxford, England: Irvington, 1975.
Mccorkle, B. H., Rogers, E. S., Dunn, E. C., Lyass, A. and Wan, Y. M., "Increasing social support for individuals with serious mental illness: evaluating the compeer model of intentional friendship," Community Mental Health Journal, Vol. 44, No. 5:359-366, 2008.
Mcmullan, M., "Patients using the Internet to obtain health information: How this affects the patient–health professional relationship," Patient Education and Counseling, Vol. 63:24–28, 2006.
Patterson, P. and Yu, T., "Understanding Customer Engagement in Services," Proceedings of ANZMAC 2006 Conference, Brisbane, 4-6 December.
Sun, Y., Lim, K. H., Jiang, C., Peng, J. Z. and Chen, X., "Do males and females think in the same way? An empirical investigation on the gender differences in Web advertising evaluation," Computers in Human Behavior, Vol. 26, No. 6:1614-1624, 2010.
Swift, D. L., Johannsen, N. M., Lavie, C. J., Earnest, C. P. and Church, T. S., "The role of exercise and physical activity in weight loss and maintenance," Progress in Cardiovascular Diseases, Vol. 56, No. 4:441-447, 2014.
Thoits, P. A., "Stress, coping, and social support processes: where are we? What next?," Journal of Health & Social Behavior, Vol. Spec, No. 1:53-79, 1995.
Van Doorn, J., Lemon, K. N., Mittal, V., Pick, D., Pirner, P. and Verhoef, P. C., "Customer Engagement Behavior: Theoretical Foundations and Research Directions," Social Science Electronic Publishing, Vol. 13, No. 3: 253-266, 2010.
Wu, H. L., Naiji. "How Your Colleagues' Reputation Impact Your Patients' Odds of Posting Experiences: Evidence from an Online Health Community," Electronic Commerce Research and Applications, Vol. 18:16-25, 2016.
Wu, J., Fan, S. and Zhao, J. L., "Community Engagement and Online Word of Mouth: An Empirical Investigation," Information & Management, Vol. 55, No. 2:258-270, 2018.
Xiao, N., Sharman, R., Rao, H. and Upadhyaya, S., "Factors Influencing Online Health Information Search: An Empirical Analysis of a National Cancer-Related Survey," Decision Support Systems, Vol. 57:417-427, 2012.
Yan, L. and Tan, Y., "Feeling Blue? Go Online: An Empirical Study of Social Support Among Patients," Information Systems Research, Vol. 25, No. 4:690-709, 2014.
Yan, L., Tan, Y. and Peng, J., "Network dynamics: how can we find patients like us?," Information Systems Research, Vol. 26, No. 3:1-17, 2015.
Yang, H., Guo, X. and Wu, T., "Exploring the influence of the online physician service delivery process on patient satisfaction," Decision Support Systems, Vol. 78:113-121, 2015a.
Yang, H., Guo, X., Wu, T. and Ju, X., "Exploring the effects of patient-generated and system-generated information on patients' online search, evaluation and decision," Electronic Commerce Research and Applications, Vol. 14, No. 3:192-203, 2015b.

Zhang, X., Guo, X., Lai, K.-H., Yin, C. and Meng, F., "From offline healthcare to online health service: The role of offline healthcare satisfaction and habits," Journal of Electronic Commerce Research, Vol. 18, No. 2:138-154, 2017.

Zhang, Z., Li, H., Meng, F. and Qiao, S., "Gender difference in restaurant online booking timing and the moderating effects of sell-out risk and information type," Journal of Electronic Commerce Research, Vol. 19, No. 3: 266-279, 2018.

Zheng, X., Cheung, C. M. K., Lee, M. K. O. and Liang, L., "Building brand loyalty through user engagement in online brand communities in social networking sites," Information Technology & People, Vol. 28, No. 1: 90-106, 2015.

Zhijun Yan, T. W., Yi Chen, Han Zhang. "Knowledge sharing in online health communities: A social exchange theory perspective," Information & Management, Vol. 53, No. 5:643-659, 2016.

Zhou, Z., Jin, X. L. and Fang, Y., "Moderating role of gender in the relationships between perceived benefits and satisfaction in social virtual world continuance," Decision Support Systems, Vol. 65, No. 1:69-79, 2014.

Ziebland, S., Chapple, A., Dumelow, C., Evans, J., Prinjha, S. and Rozmovits, L., "How the internet affects patients' experience of cancer: a qualitative study," British Medical Journal, Vol. 328, No. 7439:564-569, 2004.

Appendix A

The screen shot of online health community