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How COVID-19 Affects the Willingness of the Elderly to Continue to Use the Online Health Community:
A Longitudinal Survey

Yiming Ma, Hefei University of Technology, China, & School of Health Management Anhui Medical University, China
https://orcid.org/0000-0003-2099-8077

Yadi Gu, Center for Mental Health Education, University of Shanghai for Science and Technology, China

Wenjia Hong, Hefei University of Technology, China

Zhao Shu Ping, Hefei University of Technology, China*

Changyong Liang, Hefei University of Technology, China

Dongxiao Gu, Hefei University of Technology, China

ABSTRACT

In response to the COVID-19 outbreak, the governments of different countries adopted restrictions, such as locking down cities and restricting travel and social contact. Online health communities (OHCs) with specialized physicians have become an important way for the elderly to access health information and social support, which has expanded their use since the outbreak. This paper examines the factors influencing elderly people's behavior in terms of the continuous use of OHCs from a social support perspective to understand the impact of public health emergencies. Research collected data from March to April 2019, February 2020, and August 2021 in China. A total of 189 samples were collected and analyzed by using SmartPLS. The results show that (1) social support to the elderly during different stages has different influences on their sense of community and (2) the influence of the sense of community on the intention to continuously use OHCs also seems to change over time. The results of this study provide important implications for research and practice related to both OHCs and COVID-19.

KEYWORDS

Continuous Use Intention, Elderly, Online Health Community, Sense of Online Community, Social Support

INTRODUCTION

In January 2020, the outbreak of COVID-19 and its prevalence around the world posed a great threat to the lives and health of human beings, triggering a global public health crisis. In response to the epidemic, the governments of different countries adopted intervening measures to control the spread of the virus, such as the lockdown of cities and restrictions on travel and social contact (Bedford et al., 2020; Tian et al., 2020). These measures have been effective in controlling the spread of the virus, but have also forced people to stay at home. Older people with underlying illnesses cannot acquire offline professional medical advice during a quarantine period (Armitage & Nellums, 2020). The

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*Corresponding Author

difficulties in accessing adequate health information and social support from offline sources drives the elderly to increase their use of the Internet (Yang et al., 2020).

Online health communities (OHCs) with specialized physicians have become an important way for the elderly to access health information and social support. During the COVID-19 outbreak, many Chinese OHCs have also provided people with more convenient access to professional medical consultation services in various ways. The inability of elderly people to use traditional methods of medical consultation due to a quarantine policy promotes the continued use of OHCs by elderly people. Also, the use of OHCs is an effective way for the elderly to obtain online social support (Yan, Wang, Chen, & Zhang, 2016). Online social support is effective in improving the level of mental health of the elderly during a quarantine period (Chen et al., 2020). Therefore, the use of OHCs during the COVID-19 outbreak is significant for the elderly.

Impacted by their ability to gain access to digital resources (Armitage & Nellums, 2020), the elderly have difficulty accepting or using OHCs, compared to other age groups, and their continuous use intention (CUI) is low. Makai et al. showed that the main reasons why elderly people do not use OHCs are a lack of necessary computer skills and a preference for traditional methods of medical consultation (Makai et al., 2014).

Previous studies have examined the continuous use behavior of the elderly regarding OHCs from different perspectives (Gu, Yang, Li, Jain, & Liang, 2018). However, the outbreak of COVID-19 and the implementation of quarantine measures can also promote the acceptance and continuous use of OHCs. Studies such as those on H1N1 have shown that the emergence of public health incidents significantly increases an individual's use of online communities (Schulz, Jonker, & Faber, 2018). For example, Roberts et al. (2017) analyzed online information and showed that when people were threatened by Ebola, the use of OHCs increased (Roberts, Seymour, Fish, Robinson, & Zuckerman, 2017). However, this kind of promotion and use is coercive in nature. Therefore, a longitudinal timeline-based comparison is needed to understand the impact of public health emergencies on the continued use of OHCs among the elderly. The existing research does not answer the following questions:

1. What are the differences in the use of OHCs by elderly people before and after the COVID-19 outbreak?
2. How has online social support influenced elderly people's sense of an OHCs before and after the COVID-19 outbreak?
3. How has the sense of an OHCs influenced elderly people's continuous use behavior regarding OHCs before and after the COVID-19 outbreak?

This study examines the differences in social support, sense of online community (SOC), and the CUI of the elderly toward OHCs during different time periods. Our research collected and analyzed relevant data before, during, and after COVID-19 outbreaks to explore the above questions. It is helpful to compare the differences in the SOC and the intention to use OHCs among the elderly during public health emergencies and during non-emergency times. The data can help governments and other agencies assess the impact of COVID-19. In addition, this research can help OHCs improve the content and quality of their services in response to the continuing COVID-19 epidemic.

THEORETICAL BACKGROUND AND RESEARCH HYPOTHESES

Online Health Communities and Continuous Use Intention (Cui)

The OHCs is a type of online community. Users share knowledge, and member exchanges and other activities occur in the community, about health- or treatment-related issues (Wu & Lu, 2016). In contrast with traditional doctor-centered medical and health service model, OHCs provide users with an open network service platform for experience sharing, information exchange, and asking questions on health care–related issues (Xu, Wu, & Chen, 2022). OHCs with professional doctors also reduce the cost to patients seeking health information and medical assistance, and provide hospitals with opportunities to expand their market. The information released in OHCs includes two kinds: patients' descriptions of their own conditions and treatment histories, and the relevant answers and medical knowledge of professional doctors (Yan et al., 2016). This information is significant for users to reference, to estimate their condition related to the disease, make decisions about treatment, and choose treatment options.

With the rapid development of OHCs, a large number of scholars have conducted research on users' intention to use them. Previous research shows that users in an online health information community are more concerned about the source, accuracy, update time, and privacy of the information shared (Zhang et al., 2017). These factors are important factors that affect users' satisfaction and intention to use OHCs (Chang, Hsu, Hsu, & Cheng, 2014). In addition, some researchers have studied the intention to use OHCs in terms of technology acceptance (Yang Zhao, Ni, & Zhou, 2017), information quality (Fan & Lederman, 2017), and user participation (Fullwood et al., 2019). The existing research mainly focuses on the acceptance and satisfaction of users in the OHCs, and some researchers have studied their CUI (Stragier, Abeele, Mechant, & De Marez, 2016); however, there is a lack of research on the intention of the elderly to use OHCs and the impact of public health emergencies on their CUI.

Social Support

Social support is defined as the assistance that an individual can obtain from his personal network (Yibai Li & Wang, 2018). For the elderly, social support is of even greater significance. It can not only improve the quality of life and subjective well-being of the elderly, but also alleviate chronic diseases, extend life expectancy (Houttekier et al., 2010), and improve the quality of life (Alsubaie, Stain, Webster, & Wadman, 2019).

With the development of information and communications technology, online social support has emerged and developed into an important part of people's lives (Trepte, Reinecke, & Juechems, 2012). Online social support is social support obtained through the Internet. It is similar to offline social support (Quan-Haase, Mo, & Wellman, 2017), which can provide individuals with corresponding resources and care and can be used as a supplement to offline social support (Trepte et al., 2012). Moreover, online social support can also provide individuals with different types of support. The types of social support include emotional support, companionship support, information support, and material support (Keating, 2013). The social support that individuals obtain from social media is mainly emotional support and information support (Yuehua Zhao & Zhang, 2017). And the elderly can obtain information support and family support by using smartphones (Petrovcic, Fortunati, Vehovar, Kavcic, & Dolnicar, 2015). Studies by different scholars have confirmed that OHCs can also provide patients with corresponding online social support, including information support (Rueger, Dolfsma, & Aalbers, 2020), emotional support (Loane & Dalessandro, 2013), and companionship support (Setoyama, Yamazaki, & Namayama, 2011).

Online Social Support and SOC

SOC refers to an individual's mental state of belonging to a certain virtual community collection (Blanchard, 2007). The care, interaction, and information sharing among members of the community can provide different types of social support for online community members (Oconnor, Longman, White, & Obst, 2015). Social support affects individuals' SOC. The different dimensions of online social support (emotional support, companionship support) can affect users' life satisfaction and can improve their SOC (Oh, Ozkaya, & Larose, 2014). The survey of Pfeil, Zaphiris, and Wilson showed the correlation between online social support of the elderly and SOC; obtaining online social support can improve the SOC of the elderly (Pfeil, Zaphiris, & Wilson, 2009). For the elderly, the choice and use of online communities are largely determined by the need for social support. Online information support will affect the use of online communities by the elderly (Li et al., 2018).

As a type of online community, OHCs also provide social support that can improve SOC. For example, a study by Obst and Stafurik found that for people with disabilities, different types of social support (emotional support, information support, companionship support) provided by OHCs can improve their life satisfaction and increase their SOC (Obst & Stafurik, 2010). Access to different types of social support is an important reason for the elderly to adopt OHCs; peer support and information support obtained in the community help the elderly build a SOC (Litchman, Rothwell, & Edelman, 2017). At the same time, research on public emergencies has shown that social support can increase the individual's SOC and improve the individual's mental health during disasters. For example, a survey of elderly people after the Wenchuan earthquake showed that social support can improve SOC, and the SOC and sense of belonging can effectively reduce depression caused by disasters (Yawen Li, Sun, He, & Chan, 2011). In a recent study on COVID-19, Son suggested that by building an OHC, the elderly's social support and SOC should improve (Son et al., 2020).

We believe that during different periods, including during public health emergencies, different dimensions of online social support will affect the SOC of the elderly in online communities. Therefore, we propose the following hypotheses:

- **Hypothesis 1a (H1a).** The emotional support that elderly people receive from OHCs will positively affect their SOC.
- **Hypothesis 1b (H1b).** The information support that elderly people receive from OHCs will positively affect their SOC.
- **Hypothesis 1c (H1c).** The companionship support that elderly people receive from OHCs will positively affect their SOC.

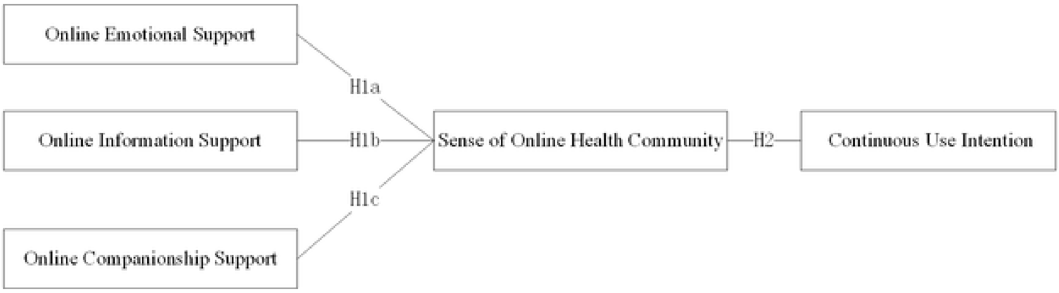
Sense of OHCs and CUI

CUI is defined as an individual's perception of the intention to continue using a certain technology or product in the future (Hoehle & Venkatesh, 2015). For members of online communities, the SOC often affects the individual's CUI in many ways (Naranjo-Zolotov, Oliveira, Casteleyn, & Irani, 2019). On the one hand, people's continuous use behaviors depend on their user experiences. SOC will increase the individual's identification with the community's identity (Pan, Lu, Wang, & Chau, 2017). Tsai and Hung confirmed that individuals continued use of an online community often comes from their identification with that community (Tsai & Hung, 2019). In addition, continuous use behavior based on identity tends to last for a long period of time (Tsai & Hung, 2019). Especially, for the elderly with underlying diseases, a strong SOC will significantly increase their continuous intention to use an OHCs (Litchman et al., 2017). On the other hand, a SOC will also promote the formation of individual usage habits, which will increase an individual's CUI (Naranjo-Zolotov et al., 2019). Individuals' habits of using online communities often affect individuals' CUI (Mouakket, 2015). Veeramootoo, Nunkoo, and Dwivedi showed that an individual's CUI will be affected by habit, and that the influence is decisive (Veeramootoo, Nunkoo, & Dwivedi, 2018). For members of OHCs, the perceived effectiveness of health information can increase their SOC, help them form good health habits, and increase their CUI (Lehto & Oinaskukkonen, 2015). Wu showed that the effectiveness of the information provided by OHCs can promote continuous use by community members (Wu, 2018). In addition, in public health emergencies, online communities can provide individuals with effective health information and enhance individuals' coping capabilities (Roberts et al., 2017), which also promotes individuals' CUI. We believe that public health emergencies may have the same impact on the elderly. Therefore, we propose the following hypothesis:

- **Hypothesis 2 (H2).** The elderly's increased SOC can increase their CUI toward OHCs.

Based on the above hypotheses, we constructed a model of the CUI of the elderly to use OHCs. The different dimensions of online social support affect the sense of belonging of the elderly in the online community. The SOC affects the CUI. Figure 1 shows the model.

Figure 1. Research model



RESEARCH METHODOLOGY

Scale Development

In this study, the main measurement variables included online information support, online emotional support, online companionship support, SOC, and CUI. Table 1 lists the measurements of seven potential variables. The questionnaire adopts the form of a Likert seven-point scale.

The social support scale was based on the study of Leung and Lee and adapted according to the actual situation (Leung & Lee, 2005). In this study, there were 11 items in the online social support scale, including four items for online emotional support (OES), four items for online information support (OIS), and three items for online companionship support (OCS).

SOC is based on the research of Sum et al. and adapted according to the actual situation (Sum, Mathews, Pourghasem, & Hughes, 2009). In this study, there were three items about community awareness, including two forward-coded items and one reverse-coded item.

CUI was based on the research of Bhattacherjee and adapted according to the actual situation (Bhattacherjee, 2001). In this study, there were three items about CUI, including two forward-coded items and one reverse-coded item.

Data Collection

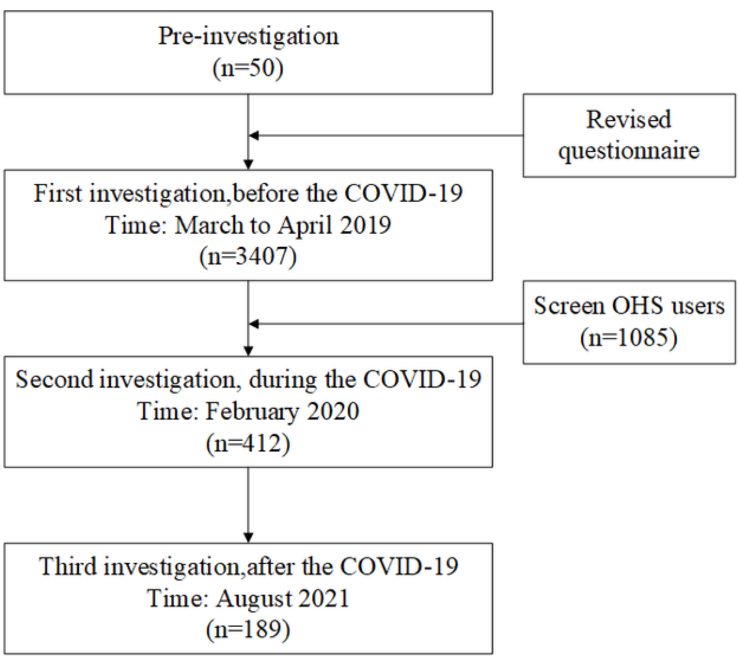
This study collected first-hand data by means of a questionnaire survey and conducted an empirical analysis. There were multiple steps to the data collection. Figure 2 shows the data collection process. First, a preliminary survey was conducted in Hefei, in the Anhui province of China, via offline distribution. The questionnaire was revised according to the results. The formal questionnaire was then distributed online using WeChat. The interval between each questionnaire collection period was eight months.

The first questionnaire was collected from March to April 2019, and the respondents were over 55 years old. When the questionnaire was completed, the respondent was entered in a raffle drawing as a reward. A total of 3,407 questionnaires were recovered. In the questionnaire, we specifically asked the subjects about their OHCs use experience. Excluding subjects without OHCs experience, 1,085 valid questionnaires were collected, with an effective rate of 31.8%. The second questionnaire was collected in February 2020. We sent questionnaires to the elderly who had reported OHCs use experience in the first survey. A total of 1,085 questionnaires were issued, and 412 were recovered, with a recovery rate of 37.9%. The third questionnaire was collected in August 2021. A total of 412 questionnaires were issued and 189 were recovered, with a recovery rate of 45.9%. The sample statistics are shown in Table 1.

Table 1. Sample statistics

	Type	Number	Proportion
Gender	male	93	49.2%
	female	96	50.8%
Age	50–59 years old	79	41.8%
	60–69 years old	62	32.8%
	70–79 years old	36	19%
	over 80 years old	12	6.4%
Education	primary school	62	32.8%
	junior school	64	33.9%
	senior school	24	12.7%
	undergraduate	29	15.3%
	master and above	10	5.3%
Income (USD)	<250	37	19.6%
	250–500	48	25.4%
	500–750	41	21.7%
	750–1,000	36	19.0%
	>1,000	27	14.3%

Figure 2. Data collection process



RESULTS

Measurement

The main analysis and verification method used in this article is partial least squares (PLS). Hair (2012) believes that in exploratory research, compared with other methods, PLS has relatively loose requirements for the normal distribution of sample data, and has higher flexibility in dealing with missing data (Gu, Deng, Zheng, Liang, & Wu, 2019). And compared with the general structural equation model, PLS has less limitation on the sample size. Therefore, PLS will be more applicable. This article uses SPSS22 (IBM, USA) and SmartPLS 3.2.8 (Boenningstedt, Germany) software for data analysis.

Table 2 shows the factor loading, composite reliability (CR), average variance extraction (AVE) and Cronbach's alpha. The value of the factor load ranged from 0.801 to 0.928, which is higher than 0.7, indicating that the observed variables have high convergent validity (Hair, Risher, Sarstedt, & Ringle, 2019). The value of Cronbach's alpha should be above 0.7, and the Cronbach's alpha coefficient ranged from 0.86 and 0.89, which shows that the measures are internally consistent. The CR value is between 0.915 to 0.924, which is higher than 0.7, indicating that the questionnaire has good convergence validity. All AVE values are greater than 0.5, indicating that the observed items explain the variance more than the error term, and that the model aggregation validity is relatively high.

Table 3 shows that the square root of each factor AVE value is greater than the other factor correlation coefficients, indicating that the questionnaire had good discriminant validity. According to Henseler et al., the heterotrait–monotrait ratio of correlations (HTMT) is another way to assess discriminant validity (Henseler, Ringle, & Sarstedt, 2015). HTMT values of less than 0.85 indicate that discriminant validity has been ascertained. In Table 4, all the HTMT values are less than 0.85. In summary, the model has good reliability and validity.

Table 2. Reliability and validity

Construct	Item	Loading	Alpha	CR	AVE
CUI	CUI1	0.868	0.890	0.924	0.754
	CUI2	0.876			
	CUI3	0.908			
OCS	OCS1	0.863	0.869	0.920	0.792
	OCS2	0.904			
	OCS3	0.885			
OES	OES1	0.851	0.890	0.924	0.752
	OES2	0.861			
	OES3	0.890			
	OES4	0.866			
OIS	OIS1	0.801	0.860	0.915	0.782
	OIS2	0.899			
	OIS3	0.895			
	OIS4	0.874			
SOC	SOC1	0.852	0.860	0.915	0.781
	SOC2	0.888			
	SOC3	0.928			

Table 3. Reliability and validity test

	OIS	SOC	OES	CUI	OCS
OIS	0.868				
SOC	0.647	0.89			
OES	0.663	0.596	0.867		
CUI	0.63	0.494	0.583	0.884	
OCS	0.657	0.577	0.667	0.574	0.884

Table 4. Heterotrait–monotrait ratio of correlations (HTMT) criterion

	OIS	SOC	OES	CUI	OCS
OIS					
SOC	0.73				
OES	0.745	0.673			
CUI	0.719	0.567	0.664		
OCS	0.752	0.663	0.762	0.665	

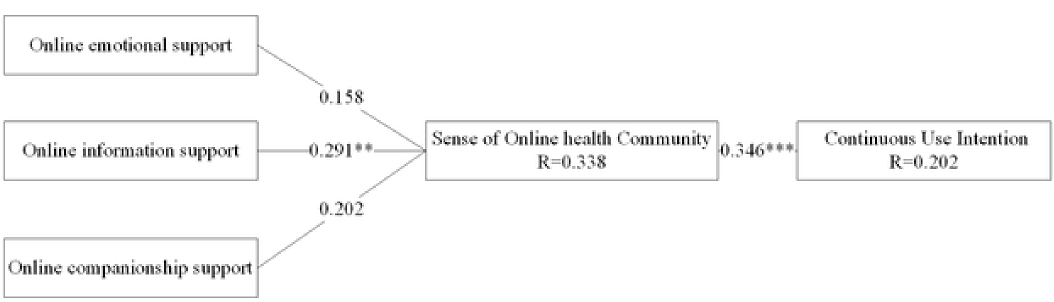
STRUCTURAL MODEL

In this study, the theoretical model proposed by SmartPLS 3.2.8 is used for structural equation analysis. The bootstrapping procedure was run with 5,000 subsamples. We tested the data collected at three different times.

Model 1: Before the COVID-19 Outbreak

The first data collection period was from March to April in 2019, and the analysis results are shown in Figure 3 and Table 5.

Figure 3. Model 1 results



* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 5. Hypothesis testing results of Model 1

Hypothetical Path	Path Coefficient (β)	T-value	Conclusion
H1a: OES ® SOC	0.158	1.787	No support
H1b: OIS ® SOC	0.291	3.219	Support
H1c: OCS ® SOC	0.202	1.909	No support
H2: SOC ® CUI	0.346	4.32	Support

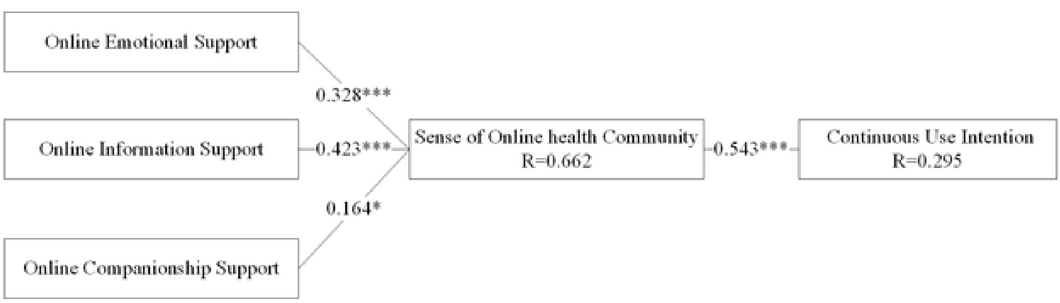
To better picture the predictive power of the theoretical model, we also calculate the effect of F^2 values to evaluate whether they affect the model's endogenous variables (Umrani, Mahmood, & Ahmed, 2016). Cohen suggests that F^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Umrani et al., 2016). In this model, the values of H1a, H1c, H1cb, and H2 are all larger than 0.02: 0.020, 0.051, 0.024, and 0.136, respectively.

Furthermore, we tested the predictive correlation of the model using a blindfolding procedure. If the Q^2 value is greater than zero, it indicates that the model has predictive power (Henseler et al., 2015). We apply the blindfolding procedure with a distance of seven to obtain the Q^2 value. In this study, all the Q^2 values were more than zero (SOC = 0.250, CUI = 0.077), thus indicating the predictive relevance of the model.

MODEL 2: DURING THE COVID-19 OUTBREAK

The second data collection period was in February 2020, and the analysis results are shown in Figure 4 and Table 6.

Figure 4. Model 2 results



* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 6. Hypothesis testing results of Model 2

Hypothetical Path	Path Coefficient (β)	T-value	Conclusion
H1a: OES ® SOC	0.328	3.843	Support
H1b: OIS ® SOC	0.423	6.071	Support
H1c: OCS ® SOC	0.164	2.276	Support
H2: SOC ® CUI	0.543	7.839	Support

In this model, all F2 values are larger than 0.02. Among them, the F2 values of H1a and H1c are larger than 0.02, at 0.133 and 0.041, respectively. The F2 value of H1b is 0.253, greater than 0.15, while that of H2 is 0.418, greater than 0.35. In addition, all the Q2 values in this model were more than zero (SOC = 0.250, CUI = 0.077), thus indicating the predictive relevance of the model.

MODEL 3: AFTER THE COVID-19 OUTBREAK

The last data collection period was in August 2020, and the analysis results are shown in Figure 5 and Table 7.

Figure 5. Model 3 results

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 7. Hypothesis testing results of Model 3

Hypothetical Path	Path Coefficient (β)	T-value	Conclusion
H1a: OES ® SOC	0.240	2.458	Support
H1b: OIS ® SOC	0.360	3.384	Support
H1c: OCS ® SOC	0.177	1.932	No support
H2: SOC ® CUI	0.589	10.294	Support

In this model, all F2 values are larger than 0.02. Among them, the F2 values of H1a, H1b, and H1c are all larger than 0.02, at 0.047, 0.118, and 0.027, respectively. The F2 value of H2 is 0.531, greater than 0.35. In addition, all the Q2 values in this model were more than zero (SOC = 0.250, CUI = 0.077), thus indicating the predictive relevance of the model.

Finally, we analyze the effect of elderly people's CUI after adding control variables. The results all show that gender, education level, and income have no significant effect on elderly people's CUI. This means that the attribute variables have no significant effect on the empirical analysis results.

DISCUSSION, IMPLICATIONS, AND CONCLUSIONS

Discussion of Findings

This paper examines the factors influencing elderly people's behavior regarding the continuous use of OHCs from a social support perspective. We collected data in March to April 2019, February 2020, and August 2021, at three different stages of the COVID-19 outbreak. The findings show that social support to the elderly during the different stages has different influences on their SOC. Also, the influence of the SOC on the CUI of the elderly toward the OHCs also seems to change over time, in the following aspects:

First, OIS has the greatest influence on the SOC, and the influence is similar in the three different periods. This result suggests that, for elderly people, the primary role of an OHCs is to provide relevant health information. The more relevant this health information is to them, the stronger their SOC will be. This result also proves that the main purpose of elderly people's use of OHCs is to obtain information support (Litchman et al., 2017). Our findings also suggest that, during the virus outbreak, OIS for elderly people has the greatest impact on their SOC compared to the other social supports. This result also reflects the fact that, during the period of a public health emergency, elderly people's need for health information increases significantly. When an OHCs can meet this need for information, elderly people's SOC to that OHCs will increase significantly. This conclusion is similar to that of Li (2011); that is, when elderly people face a disaster, and when a community is able to meet their needs, their sense of recognition of that community increases (Yawen Li et al., 2011).

Second, OES has different influences on the SOC during different periods. The influence of OES is no significant before the outbreak. And after the outbreak began, individuals in the OHCs tended to have the same emotional needs out of their fear of COVID-19; they needed to relieve their fear about COVID-19 and encourage each other. This result also confirms Hu, Zha, and Yan's conclusion that online community members interact more frequently when a public health emergency occurs (Hu, Zha, & Yan, 2020). This increased interaction leads to a significant increase in the level of emotional support and also increases the users' recognition of the OHCs. Our study also shows that the influence of emotional support gradually decreases after the epidemic, which also indicates a decrease in the frequency of OHCs interactions.

Third, OCS influences the SOC only during the epidemic. This research finding is somewhat different from that of past studies (Litchman et al., 2017; Obst & Stafurik, 2010; Oh et al., 2014). Most research shows that OCS influences the SOC in a general environment. We conclude that the reason for our different finding is the difference in research subjects. Most elderly people are more inclined to obtain offline companionship support. Only when companionship support cannot be obtained offline do they obtain it online. During the outbreak of COVID-19, people were confined to their homes due to quarantine policies, which made it difficult for elderly people to obtain companionship support offline. Under such a circumstance, elderly people who use OHCs attempt to obtain companionship support online. When the quarantine policy is lifted and the elderly people are free to move around, they will quickly abandon online social support. This research finding validates Wang, Zhao, and Street's research (2017) on social support in OHCs (Wang, Zhao, & Street, 2017).

Last, our study shows that the SOC significantly influences the CUI. This influence increases with the time of use. The research on three points of time suggests that, when elderly people use OHCs continuously, they gradually gain a stronger SOC, and their CUI is influenced. We conclude that, when elderly people use OHCs for a long time and benefit from them, the use habit they develop gradually increases their SOC. This confirms the findings of previous studies (Mouakket, 2015; Naranjo-Zolotov et al., 2019; Veeramootoo et al., 2018). Our study also shows that the outbreak of COVID-19 does not significantly influence either of them. This result suggests that the influence of the SOC on the behavior of continuous use is mainly related to the time of previous use.

Implications for Research

This study makes a theoretical contribution to the study of online social support and OHCs.

First, by comparing data from before and after the epidemic, we find the change in the influence of online social support on the SOC to the OHCs. Previous studies mainly discuss the influence of online social support during normal situations (Greene, Choudhry, Kilabuk, & Shrank, 2011; Petrovcic et al., 2015). In the present study, by comparing research findings during different time periods, we find changes in elderly people's need for online social support. The results of this study show the influence of quarantine policies on elderly people's social support needs, which is new research finding that contributes to our understanding of the impact of COVID-19 on the elderly.

Our study also confirms the difference in the need for online social support between the elderly and other age groups. The elderly is more inclined to obtain companionship support from offline sources than other age groups are. Therefore, this study reveals how elderly people's need for social support changes during different conditions. It also shows the characteristics of elderly people's need for social support during public health emergencies, hence enriching the theory of social support under specific contexts.

Second, our study confirms that the SOC has an influence on the CUI. The influence is mainly related to the time of use (Stragier et al., 2016). As a time, sequence study, we compared the influence of the SOC on elderly people's continuous use of OHCs before and after the epidemic. The results show that the influence of the SOC on the CUI is not always the same. When an individual uses an OHCs for more time, the influence of the SOC on the CUI is gradually stronger. This research finding enriches the research on the CUI, fills the blank spaces of previous studies, and provides a theoretical basis for subsequent relevant studies.

Finally, our study has, through comparison, also examined the impact of COVID-19 on the elderly. As a necessary epidemic prevention measure, the quarantine policy was effective in stopping the spread of the epidemic (Bedford et al., 2020; Tian et al., 2020). However, the policy harmed elderly people, as it reduced the level of offline social support available to them. Our research subjects were elderly people with access to the Internet; we suspect that the policy may be even more harmful to elderly people who are unable to use the Internet or do not have access to it. This important finding provides a theoretical basis for us to be able to properly understand a series of social issues arising from COVID-19.

Implications For Practice

As the elderly population increases in many countries, the health issues of the elderly become many people's major concern. By comparing the differences before and after the epidemic, our study can make the following practical recommendations. First, government departments should consider the elderly during public health emergencies, to reduce their mental pressure. They should offer the elderly timely care and assurance, and provide effective social support to the elderly. Second, OHCs developers should improve the user interface and provide a more convenient operating interface for the elderly, in order to improve elderly people's ability to use information and communication technology. They should use the Internet of Things, mobile health, and other technologies to obtain health data (Gu et al., 2020). This strategy can help the elderly communicate better with doctors and provide them with more accurate medical information. At the same time, effective information support can be provided specifically for the elderly, such as by creating a forum or a post dedicated to serving the elderly. The OHCs should work to increase the amount of time elderly people spend using the online community, so that the elderly become more willing to continuously use it. Finally, elderly people need to broaden the ways in which they access social support, especially online social support.

LIMITATIONS AND FUTURE DIRECTIONS

This is a comparative study on elderly people's SOC and CUI, from a time sequence perspective. This study has theoretical and practical value, but some problems also exist. First, our research subjects were the elderly population in China; in future research, the focus of the research could be the CUI of elderly populations in different countries and with different cultural backgrounds, to study their continuous use of OHCs. Second, CUI is influenced by many factors, and SOC is only one of them. Therefore, future studies will be conducted from more perspectives. Last, the time span of this study is only sixteen months, which does not fully reflect the trajectory of change in the subjects' CUI, especially after the epidemic. Therefore, we will continue to follow up with the research subjects to understand the change in their CUI in the future.

CONCLUSION

With the rapid development of OHCs, how to improve people's willingness to continuously use them has become an important research issue. For the elderly, as a vulnerable group, the use of OHCs during public health emergencies has great significance. This paper is based on the theory of social support, it reveals the changes of each dimension of social support over time and comparing each dimension's influence on the sense of belonging to an OHCs. And we also studied the influence of SOC on CUI in different periods. It contributes to the development of the theory of community health and social support, and puts forward corresponding suggestions. We hope that these recommendations will help with the development of OHCs and coping with COIVD-19.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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Yiming Ma is a Ph.D. in the School of Management, Hefei University of Technology (HFUT). He obtained an MBA degree in York St John University. His research interests focus on aging care, social media, human-computer interaction, mental health, and health management. He has published five papers in journals and conferences, and published an MBA case.

Wenjia Hong is a Ph.D. candidate in the School of Management at Hefei University of Technology (HFUT). She is doing research in the use of Artificial Intelligence, with a particular focus on the smart elderly care. Specifically, she is interested in the behavioral studies of Artificial Intelligence's role in different individuals, groups and organizations, and the mental health of the elderly .

Shuping Zhao received the PhD in business administration from Hefei university of Technology, Hefei, China, in 2015. Currently, he is a associate Professor of Management Information Systems at Hefei University of Technology. He has published over 10 papers in journal. He main research interests are decision-making theory and data mining.

Changyong Liang is a professor of MIS and Director of the Institute for the IT Management at HFUT. He is the vice Dean of Academy of Science & Research at HFUT. He received his Ph.D. in management science and engineering from the Harbin Institute of Technology. Dr. Liang received National Scientific and Technological Progress Award of China and the Ministry of Education' Science Prize of China in 2008. He is a member of the Ministry of Education' Teaching Steering Committee for Management Science and Engineering Related Majors, executive committee members of CNAIS, and committee member of China Management Science and Engineering Society. He is also the associate editor in chief of the Chinese Journal of Management Science. He is the co-chair for the 9th China Summer Workshop on Information Management (CSWIM2015). Dr. Liang has over 30 years of experience in examining, analyzing, designing, evaluating, developing, and implementing various information systems for enterprises, hospitals, and governments. His research focuses on information management, the role of emerging technologies such as cloud computing in smart business and society. He is an author/editor of 7 books and over 130 publications in high-level journals or conference proceedings.

Dongxiao Gu is an associate professor of Management Information Systems in the School of Management at HFUT where he obtained his Ph.D. and M.S. He received his B.S. in MIS from Jilin University. Dr. Gu held visiting scholar positions in Indiana University Bloomington in 2018 and the University of Wisconsin-Milwaukee in 2010. His research interests focus on cloud computing, medical big data analytics, health intelligence, and health management. Dr. Gu received Emerald LIS Research Highly Commented Award of China and the best paper nomination of Wuhan International Electronic Commerce Conference in 2016. He is an author/editor of 6 books and over 80 publications in journals/proceedings such as Bulletin of Chinese Academy of Sciences, Information & Management, Computers & Industrial Engineering, International Journal of Medical Informatics, International Journal of Production Research, International Journal of Project Management, Applied Soft Computing, Expert Systems with Applications, Knowledge-Based Systems, and etc. He serves on the editorial board of Data Intelligence hosted by CAS and MIT. He is a council member of China Association for Information (CNAIS).