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RESEARCH ARTICLE

Physicians' Prosocial Behavior and Consultation Volume in an Online Health Community: A Longitudinal Analysis

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ABSTRACT

In online health communities (OHCs), physicians' prosocial behavior can bring numerous benefits to both platforms and patients. By sharing health articles and videos, providing free live diagnoses, physicians can contribute to improved health outcomes, enhanced trust, and the prosperity of OHCs. However, few studies have been conducted to examine the impact of prosocial behavior on consultation volume in the OHC field. This study aims to investigate the influence of physicians' prosocial behavior on consultation volume in OHCs. Additionally, the authors are interested in exploring the role of physicians' online popularity in the relationship between prosocial behavior and online consultation volume. Guided by signaling theory, social exchange theory, social capital theory, this study developed hypotheses and an econometric model. Subsequently, a fixed-effect regression was employed to test these hypotheses using panel data comprising 1,015 hepatitis B physicians and 1,052 lung cancer physicians from Haodf.com, a prominent OHC in China. The descriptive statistical analysis, correlation analysis, regression analysis, robustness checks, endogeneity test were conducted using stata. The results indicated that both the quantity and quality of physicians' prosocial behavior had a positive impact on consultation volume (β=.075, P<.001; β=.124, P<.001). Furthermore, the quantity and quality of prosocial behavior also positively influenced physicians' online popularity (β=.083, P<.001; β=.148, P<.001). When physicians' online popularity was included in the model, the quantity and quality of prosocial behavior, as well as online popularity, all showed positive and significant effects (β=.032, P=.001; β=.034, P=.02; β=.555, P<.001). In conclusion, physicians' prosocial behavior has a positive impact on consultation volume, and this effect is partially mediated by their online popularity. These findings are applicable to chronic physicians, regardless of the severity of the disease. This paper is the first to elaborate how physicians' prosocial behavior affects consultation volume from the perspective of follower interaction.

INTRODUCTION

Prosocial behavior refers to behavior that benefits others or society (Jing et al., 2019), such as voluntary actions (Wilson, 2012) and charitable donations (Bekkers and Wiepking, 2011). In fact, similar behavior also exists in online health communities (OHCs). Physicians in OHCs not only engage in economic activities, such as written/telephone/video consultation, team consultation and private doctor service (Chen et al., 2020), but they also perform prosocial behavior (Wang et al., 2022). For example, physicians upload health articles and medical videos, provide free live diagnoses, and share typical medical cases. The kindness and integrity contained in prosocial behavior can be conveyed to patients, potentially improving their consultation decision.

With the development of internet technology, OHCs have made rapid progress in recent years (Goh et al., 2016; Wu et al., 2019). The trend reached its peak during the outbreak of the COVID-19 when people needed medical care without the risk of cross-infection (Wan et al., 2021). Even as the COVID-19 epidemic subsides, people have become accustomed to online consultation. There are many OHCs in China, such as Good Doctor Online, Chunyu Doctor, Dingxiang Garden, Ali Health and Jingdong Health (Li et al., 2023; Xiong and Zhao, 2017).

To the best of our knowledge, physicians play a vital role in OHCs and domain the process of doctor-patient interaction (Liu et al., 2022; Ren and Ma, 2021). Only when physicians take initiatives in OHCs can the platform prosper sustainably (Li et al., 2020). The main motivation for physicians to sacrifice their spare time to diagnose patients online is to receive extra online economic returns. Therefore, existing studies primarily focus on factors that improve physicians' online returns, such as professional title (Li et al., 2019), online reviews (Li et al., 2023; Liu et al., 2020). However, limited research has been conducted on physicians' prosocial behavior. Prosocial behavior has been extensively studied in the corporate management (Awaysheh et al., 2020) and developmental psychology (Hay et al., 2021), but its application in OHC has been largely overlooked. While some scholars have explored the motivations behind physicians' prosocial behavior in OHC, such as professional motivation (Qi et al., 2021; Yang et al., 2021), few have examined the resulting consequences. There is a lack of studies investigating the impact of physicians' prosocial behavior on consultation volume in OHC. Engaging in prosocial behavior requires time, energy and increased expertise. Empirical research has indicated a positive relationship between effort and performance (Li et al., 2020). Following this line, we propose the following research question:

Does physicians' prosocial behavior positively impact online consultation volume?

Only a few studies have explored the relationship between physicians' prosocial behavior and their online consultation volume. Wang et al. (2022) examined this relationship from the physicians' perspective. They empirically demonstrated that the heterogeneity of physicians (high/low title/WOM) can influence how patients interpret physicians' prosocial behavior, subsequently impacting online consultation volume. However, most studies have neglected the role of physicians' online popularity. Popularity is a common metric used to evaluate product image and refers to the extent to which a product is known by the public (Liu et al., 2014). In the context of OHC, physicians' online popularity with patients can be measured by the number of followers of their popular science column (De Veirman et al., 2017) and the number of virtual gifs received (Haim et al., 2018). Previous research has demonstrated that online efforts can enhance physicians' popularity (Chien et al., 2003; McClean and Collins, 2011), and subsequent users are more likely to consider this popularity when seeking medical service (Li et al., 2020). Building upon social capital theory and social exchange theory (Li *et al.*, 2019), we aim to explore the relationship between physicians' prosocial behavior and online consultation volume from the perspective of fan interaction. Therefore, we propose the second research question:

Does physicians' online population mediate the impact of prosocial behavior on consultation volume?

To address the research gaps, we developed a conceptual model and proposed four hypotheses based on information asymmetry theory, signaling theory and reciprocity theory. We then empirically verified these hypotheses by collecting and analyzing secondary data, which included 1,015 hepatitis B physicians and 1,052 lung cancer physicians from Haodf.com, the largest OHC in China. The results indicate that physician's prosocial behavior positively influences online consultation volume, and this effect is partially mediated by physicians' online popularity. Furthermore, these findings are applicable to chronic physicians, regardless of the severity of the disease. This research contributes to the existing knowledge on prosocial behavior in the context of OHC. Additionally, for the first time, we shed lights on the impact of physicians' prosocial behavior on consultation volume from the perspective of fan interaction.

Theoretical background

Signaling theory: There exists serious information asymmetry in OHC fields. Physicians possess a higher level of professionalism due to their longer academic training in medical specialties compared with other majors. This leads to a situation where physicians have more medical knowledge than patients, resulting in a substantial information asymmetry. From the perspective of physicians, they dominate the doctor-patient interaction due to this information asymmetry (Chen et al., 2020). In some cases, physicians may recommend unnecessary services and expensive drugs to patients in order to increase their earnings, which raises ethical concerns. On the patients' side, limited health literacy makes it challenging to differentiate physicians' professional skills and service attitudes. Consequently, patients struggle to make informed consulting decisions and are unable to assess the effectiveness of their treatment. As a consequence, the information asymmetry may cause serious consequences. On the one hand, it leads to wasted time and money. On the other hand, there is a risk of delaying the diagnosis, leaving patients in danger. Therefore, it is crucial to address this issue by introducing the signaling theory.

Spence (2002) introduced signaling theory for the first time by examining information asymmetry in the labor market. This theory helps us understand how individuals behave when there is a lack of observable capabilities and hidden qualities between two parties (Moon and Shugan, 2018; Pan et al., 2013; Rao et al., 2018; Yang et al., 2020a). Signaling theory consists of three elements: signal, signaler and receiver (Connelly et al., 2011). The signaler possesses crucial information that the receiver cannot access. Signals can be categorized as positive or negative based on their content. The signaler has the power to choose which type of signal to send to the receiver. Unfortunately, signalers often intentionally send only send positive signals while hide negative ones to maximize their profit. When deciding which signals to send, the signaler must consider observability and cost. Observability determines whether the signal can be received by the receiver, while cost refers to the time, energy and expenditure required to send the signal. Both factors are crucial in the decision-making process (BliegeBird and Smith, 2005). Furthermore, according to Zmud et al. (2010), an effective signal can influence the views and behavior of the receiver. Signaling theory has been widely used in various management fields, including organizational and strategic management (Miller and del Carmen Triana, 2009), human resource management (Suazo et al., 2009) and marketing management (Moon and Shugan, 2018).

In the context of OHC, signaling theory has been extensively used to explain how patients assess the qualities of physicians and make consulting decisions (Li et al., 2019; Liu et al., 2016; Ouyang and Wang, 2022). However, there has been limited research on the application of signaling theory to study physicians' prosocial behavior. As is shown in Figure 1, signaling theory consists of three stages: signaling stage, processing stage and feedback stage. In the sigaling stage, when physicians engage in prosocial behavior in OHC, they send signals that convey their service attitudes and professional expertise to patients. In the processing stage, patients receive and interpret these signals, which helps reduce information asymmetry and facilitates their decesion-making process. In the feedback stage, patients select appropriate physicians to consult, become followers of popular science column, or even express gratitude by purchasing virtual gifts for physicians.

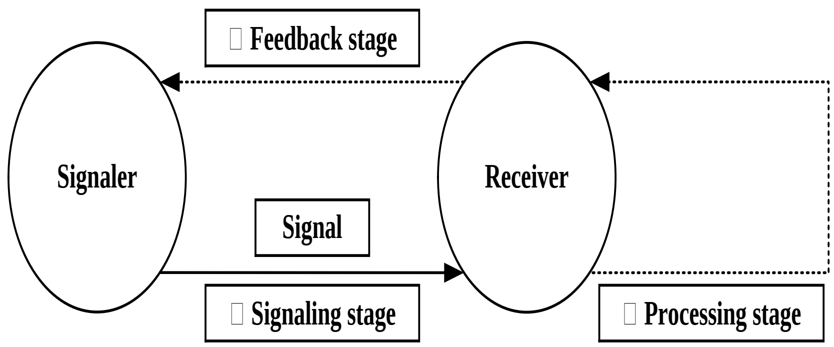

Figure 1: Signaling theory

Social exchange theory

George Homans (Homans, 1958) introduced social exchange theory in the late 1950s, which suggests that beyond mere economic transactions, there exists a social exchange behavior among individuals. Unlike strict economic exchanges, social exchanges lack formal contracts and clear obligations prior to transactions. Social exchanges stem from social attraction, with attraction influenced by the potential rewards. Peter Michael Blau (1964) further categorized social exchange into internal, external, and mixed types based on rewards. Gouldner (1960) emphasized reciprocity principle in social exchanges, where individuals receive social rewards during interactions, fostering continued engagement.

Applying social exchange theory to the doctor-patient relationship, Berg et al. (2006) view it as a unique social exchange dynamic. Physicians seek patients' approval, support, and economic gains through services, while patients desire physicians' services, assistance, relationships, and compassion. This relationship is founded on commitment and reciprocity, akin to a social exchange. Online doctor-patient interactions mirror social exchanges due to the absence of predefined obligations and rewards before services are rendered. Patients are inclined to reciprocate quality care by paying for services through intrinsic rewards like appreciation and extrinsic rewards such as online tips or additional paid services. This theory forms the basis for exploring the impact of physicians' prosocial behavior on patients' consultation decisions from a social psychology perspective.

The reciprocity principle, based on mutual indebtedness, drives ongoing communication between individuals (Chen and Hung, 2010). Engaging in prosocial behavior following the reciprocity principle can benefit physicians in the short or long term, despite potential personal sacrifices (Wang et al., 2022).

Social capital theory

Social capital theory, proposed and developed successively by Bourdieu (2018), Coleman (1994), and Leonardi et.al. (2001), has become an important research issue in the fields of economics and management. The theory mainly focuses on individual social interactions, collaborative interactions, and informal institutions. Social capital theory consists of two main research perspectives: resource elements and institutional elements. The resource element views social capital as a resource formed based on social network structures, where individuals can acquire scarce resources by establishing social relationships with others in the network. The institutional element is mainly based on the interactive communication among individuals in the network, forming an informal institution under the influence of social norms such as reputation, commitment, and reciprocal relationships. The research on social capital theory has gradually expanded to internet scenarios like online communities. In online health community, the social information generated from the interaction between physicians and patients can facilitate other patients in gathering and analyzing information, transmitting effective information, thus forming social capital on cognitive, reputational, and punitive levels. Patients consider social capital as a reliable signal, and tend to consult physicians who have higher level of social capital.

The measurement of social capital is a technical challenge in the application of this theory. Nahapiet and Ghoshal subdivided social capital into three dimensions: structure, relationships, and cognition, which essentially cover the basic characteristics of the relationship structure and resource attributes of social capital, gradually becoming the mainstream measurement method in current research. In the study of online social capital, researchers mainly follow Nahapiet and Ghoshal's three-dimensional classification framework, but still largely rely on questionnaire forms, neglecting the behavioral data of individuals on social platforms. Some studies have begun to use objective data from social platforms as proxy indicators of social capital, mainly focusing on measuring from the structural dimension, such as using the number of followers of social media users as proxy index. The measurement of relational dimension social capital mainly refers to the number of likes, comments, or rewards, which are based on the relationships generated from online interactions. The cognitive dimension of social capital reflects people's sense of values, which is not key evidence for people to choose physicians and is difficult to accurately measure. In conclusion, it is appropriate to measure online social capital from the structural and relational dimensions.

In the field of online health community, there exists severe information asymmetry. This study uses the number of followers and the number of gifts as proxy indicators for structural and relational social capital. It is crucial for increasing online consultations volume to overcome potential distrust factors. Structural social capital on social platforms serves as a vital signal in alleviating distrust, primarily reflected in the number of followers. The larger the number of followers, the higher structural social capital, leading to a greater online consultation volume. Relational social capital is a relational element embedded in social networks, representing the emotional quality in the social interaction process. Social interactions between patients and physicians, such as sending virtual gifts, can effectively enhance other patients' recognition for physicians, thereby increasing sense of trust.

Through the combined effects of word-of-mouth and herd behavior, the likelihood of consultations is increased.

Research hypotheses and conceptual model

Relationship between prosocial behavior and consultation volume

In online health communities (OHCs), physicians' prosocial behavior refers to activities such as sharing health articles, creating medical science videos, providing free live diagnoses, uploading typical medical cases, etc. Due to a lack of medical knowledge, patients are often not fully aware of their health conditions. Unlike regular commodities, medical services have a credence feature that leads to more serious information asymmetry (Dulleck and Kerschbamer, 2006). The quality of online medical services can directly impact patients' health and even their lives, making it crucial for patients to understand the professional skills and service attitudes of physicians. The strength of physicians' prosocial behavior can be measured through two dimensions: quantity and quality (Wang et al., 2022). On the one hand, if a physician engages in a large quantity of prosocial behavior, it indicates a strong willingness to provide medical services to patients, often at the expense of personal time. Furthermore, through various forms of prosocial behavior, patients can gain insights into the physician's medical specialty, which helps alleviate information asymmetry. On the other hand, high-quality prosocial behavior requires significant effort and demonstrates the physician's exceptional professional skills. In summary, a high strength (quantity and quality) of prosocial behavior helps patients understand the physician's professional skills and service attitudes, comprehend their disease and treatment plans, and ultimately make informed consultation decisions.

In addition, the doctor-patient interaction on online health community is a social exchange process rooted in physicians' prosocial behavior. Once physicians offer effective guidance to patients, leading to patient benefits, the patient will pay for the consultation to maintain this exchange, following the principle of reciprocity. Based on the above analysis, we propose the following hypotheses:

H1a: The quantity of physicians' prosocial behavior positively impacts online consultation volume

H1b: The quality of physicians' prosocial behavior positively impacts online consultation volume

Mediating effect of physicians' online popularity

Based on previous research, online popularity is typically measured by factors such as the number of followers (Jin and Youn, 2022), the number of likes or shares (Lee, 2021), the number of clicks and or comments (Haim et al., 2018). In the OHC field, we also consider the number of followers of popular science column and the number of virtual gifts as indicators of physicians' online popularity.

Hu (2020) argued that many celebrities on Tiktok, a popular short video platform in China, accumulated a large number of followers by creating high-quality content. Similarly, it can be inferred that physicians in OHCs can attract followers to their popular science column through engaging in prosocial behavior with high quantity and quality. When physicians register on an OHC platform, they automatically have their own personal homepage. They can then open a popular science column module voluntarily where they engage in prosocial activities. If patients are satisfied after a consultation, they can click the "follow" button to become a follower of the physician's popular science column. This allows patients to conveniently access health articles and newly shared videos by the physician, enhancing their understanding of their condition, adjusting their mindset in a timely manner, and developing a more targeted physical recovery plan. Additionally, patients who do not want to pay for online consultation can still choose to follow a kind-hearted and skilled physician based on the quantity and quality of their prosocial behavior, thereby increasing the number of followers of the physician's popular science column. Figure 2 illustrates an example of a physician's popular science column.

Figure 2: A sample of a physician's popular science column.

Generally speaking, gift giving has been found to be beneficial for expressing emotions and building relationships (Ruth et al., 1999). From the patients' perspective, giving gifts helps them show gratitude and kindness. From the physicians' perspective, patients spend extra money on virtual gifts, which is not included in the treatment fee. All the money goes directly to the physicians' account and without any commission taken by the platform. This increases the physicians' online returns and makes them feel respected. As a result, they may be inspired to work even harder in the future (Li et al., 2020). When patients perceive professional skills and service attitudes of physicians through their prosocial behavior, they voluntarily buy virtual gifts for them. This is similar to patients awarding thank-you flags to professional physicians in an official clinic. Therefore, it is reasonable to conclude that an increase in the strength of a physician's prosocial behavior will lead to an increase in the number of virtual gifts.

On the other hand, when a physician is perceived to have high online popularity, people tend to use the bandwagon heuristic, believing the physician is professional and approachable because others think so too (Sundar, 2008). Studies have shown that people are inclined to believe certain products or services are good or correct if others do as well (De Veirman *et al.*, 2017; Metzger et al., 2010). Yang et al. (2015) confirmed that patient-generated information can reflect the quality of physicians' service outcomes and delivery processes, helping patients to choose doctors (Cao et al., 2017). As a form of patient-generated data, physicians' online popularity is likely to influence subsequent patients when selecting a physician for consultation. First, as a type of social capital, physicians' online popularity increases the level of patients' trust. When a physician has higher online popularity, potential patients will increase their trust in the physician and are more likely to consult the doctor. Secondly, in the situation of information asymmetry or information opacity, people tend to follow the behavior of others to make decisions. In other words, under the effect of herd effect, when a physician is highly popular, other patients will follow and recognize the physician, thus improving the possibility of consultation. According to social capital theory, we speculate that physicians' online popularity is positively associated with online consultation volume.

Based on the above analysis, we propose the following hypotheses:

H2a: Physicians' online popularity plays a mediating role between the quantity of prosocial behavior and consultation volume

H2b: Physicians' online popularity plays a mediating role between the quality of prosocial behavior and consultation volume

Based on the aforementioned hypotheses, we present the conceptual model for this study, as is depicted in Figure 3.

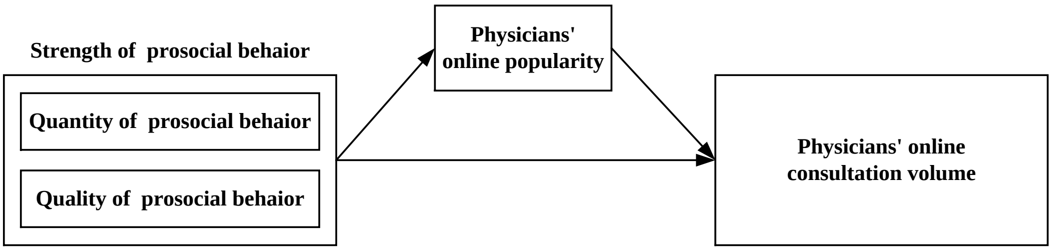

Figure 3: Conceptual model

MATERIALS & METHODS

Data description

The research was conducted on Haodf.com, a prominent OHC in China (Chen et al., 2020). Since its establishment in 2006, Haodf.com has managed to attract about 910,000 physicians from over 10,000 hospitals in major cities by 2023, and it serves around 300,000 patients daily (Zhang et al., 2020). These physicians offer a range of services, including written/phone/video consultation, appointment referral, private doctor service, team consultation, among others (Jing et al., 2019). Figure 4 present a hepatitis B physician's personal homepage.

Figure 4: A hepatitis B physician's personal homepage

In order to attract patients, physicians often engage in prosocial behavior through personal popular science column. This includes activities like uploading health articles and medical videos, providing free live diagnoses, and sharing typical medical cases. These efforts help reduce information asymmetry and enable patients to receive better online healthcare services (Wang et al., 2022).

Hepatitis B is a stigmatized and infectious chronic disease, making it suitable for repeat online consultation. These patients tend to have stronger privacy concerns and are often hesitant to visit hospital due to fears of exposing personal information and feeling embarrassment (Li et al., 2020).

For this research, a java-based web crawler was developed to collect data on hepatitis B physicians from September 22, 2022 to December 7, 2022 at intervals of every half month. Physicians who did not offer any form of online consultation service were excluded from the study. Only physicians with data for three or more sequential periods were retained. Ultimately, we obtained a six-stage panel data set consisting of 1,015 physicians and 5,783 observations.

Measurement

The dependent variable is online consultation volume (*ConVol*). It is measured by the total number of patients who have consulted the physician (Hu et al., 2021; Liu et al., 2022; Ouyang and Wang, 2022; Wan et al., 2021; Wang et al., 2022; Xing et al., 2019; Yang et al., 2020a).

The independent variables are the strength of prosocial behavior. The quantity of prosocial behavior is measured by the total number of articles ($ArtNum$). The quality of the prosocial behavior is assessed using the P-index. According to Prathap (2010), the formula for calculating the P-index is as follows: $P = (C^2/ProBeh)^{1/3}$, where C represents the total reading volume (Wang *et al.*, 2022).

The mediating variable is physicians' online popularity (Pop), which can be measured by the number of followers ($Follower$), and the number of virtual gifts ($Gift$). The number of followers represents structural social capital and the number of gifts represents relational social capital for a physician. For empirical analysis, the number of followers is used, while the number of virtual gifts is used for robust testing.

There are six control variables considered in as is shown in the table. These variables are included in the models to ensure robustness, as they can all influence patients' choices.

An overview of the variables is presented in Table 1.

Table 1: Variables description and measurement

Variables	Description	Measurement
Dependent variable		
$ConVol_{it}$	Consultation volume	The number of patients who have consulted physician i at time t
Independent variables		
$Probeh_{it}$	Quantity of prosocial behavior	The prosocial behavior volume performed by physician i, proxied by the number of health articles at time t
P_{it}	Quality of prosocial behavior	The quality of physician i's prosocial behavior at time t
Mediating variables		
Pop_{it}	Online popularity	The physician's online popularity, proxied by the number of followers of physician i's popular science column at time t
Control Variables		
$Title_{it}$	Professional title	The professional title of physician i (1 represents chief physician; 0 otherwise)
$HosLev_{it}$	Hospital level	The level of hospital physician i works in (1 represents Grade III Class A hospital; 0 otherwise)
Off_{it}	Offline appointment	Whether physician i providing offline appointment service (1 represents providing; 0 otherwise)
$Rating_{it}$	Online rating	A score rated by patients who have consulted physician i at time t
$Price_{it}$	Consultation price	The price of physician i's telephone consultation.
$Access_{it}$	Access volume	The number of calculated access volume of physician i's homepage at time t

Empirical model

In this study, the range of data fluctuates widely. We have found that the logarithmic function in mathematical functions does not change the correlation between variables. To address the issue of large variances and the problem of the zero values, we consider the logarithms of (variable+1) (Li et al., 2019). For physician i at time t, since the strength of prosocial behavior has a lag impact on online consultation volume and they have an effect on each other, which can result in endogeneity, we use the lagged one-stage value of independent variables. We developed a fixed-effect formula to estimate the main effect as follows.

$$\ln ConVol_{it+1}=\alpha_0+\alpha_1\ln ProBeh_{it}+\alpha_2\ln P_{it}+\alpha_3 control_{it}+\varepsilon_1 \qquad (1)$$

here, α parameters are the coefficients to be estimated, and ε_1 is the error term.

According to Wen and Ye (2014), we developed formula (2) and formula (3) to verify the mediating effect of online popularity.

$$\ln Pop_{it+1}=\beta_0+\beta_1\ln ProBeh_{it}+\beta_2\ln P_{it}+\beta_3 control_{it}+\varepsilon_2 \quad (2)$$

$$\ln ConVol_{it+1}=\gamma_0+\gamma_1\ln ProBeh_{it}+\gamma_2\ln P_{it}+\gamma_3\ln Pop_{it}+\gamma_4 control_{it}+\varepsilon_3 \quad (3)$$

here, β *and* γ parameters are the coefficients to be estimated, ε_2 and ε_3 are the error terms.

RESULT

THE data was analyzed using Stata version 16.0. Table 2 presents the descriptive statistics, while Table 3 shows the correlations for the key variables.

Table 2: Statistics of variables

Variable	N	mean	sd	min	max
ConVol	5783	1864.229	3939.812	0	45101
ArtNum	5783	27.263	141.222	0	3576
P	3686	712.193	616.269	1	6116.861
Off	5768	0.447	0.497	0	1
HosLev	5756	0.969	0.173	0	1
Rating	5782	3.659	0.345	3.2	5.0
Title	5763	0.689	0.463	0	1
Follower	5782	1123.988	2271.972	0	20000
Gift	5783	139.822	374.345	0	3734
Price	4013	12.000	13.087	0	200.000
Access	5783	1581441.873	5045887.549	703	85382774

Table 3: Correlations matrix

Variable	1	2	3	4	5	6	7	8	9	10	11
1.ConVol	1										
2.ArtNum	0.287	1									
3.P	0.611	0.359	1								
4.Off	0.129	-0.006	0.054	1							
5.HosLev	-0.056	-0.014	0.011	-0.025	1						
6.Rating	0.509	0.108	0.324	0.261	0.011	1					
7.Title	0.113	-0.011	0.112	-0.015	-0.080	0.104	1				
8.Follower	0.853	0.281	0.475	0.201	-0.038	0.655	0.120	1			
9.Gift	0.794	0.412	0.520	0.136	0.020	0.533	0.057	0.784	1		
10.Price	0.322	0.057	0.186	0.086	0.051	0.225	0.032	0.243	0.249	1	
11.Access	0.760	0.414	0.679	0.040	0.008	0.263	0.100	0.487	0.688	0.215	1

The largest value in the correlations matrix is 0.853, which is greater than 0.8. Therefore, we calculated the Variance Inflation Factor (VIF) statistics, as is shown in Table 4.

Table 4: VIF test

Variable	VIF	1/VIF
Gift	4.12	0.24
Follower	3.44	0.29
Access	2.84	0.35
P	2.03	0.49
Rating	1.90	0.53
ArtNum	1.30	0.77
Price	1.10	0.91
Off	1.10	0.91
Title	1.04	0.96
Image	1.04	0.96
HosLev	1.02	0.98
Mean VIF	1.90	

The VIF statistic for each variable is less than 10, indicating no significant multicollinearity among the variables (Deng et al., 2019).

Results of the main effect

To assess the impact of physicians' prosocial behavior on consultation volume, we employed fixed-effect hierarchical multiple regression. The empirical results are presented in Table 5. Model 1 solely includes control variables. Model 2 incorporates the quantity of prosocial behavior, while model 3 includes the quality of prosocial behavior. Lastly, model 4 encompasses both of the quantity and quality of prosocial behavior. In model 2, the coefficients for ln$ArtNum_{it}$ are positive and significant (β=.020, P=.008), and the same holds true for model 4 (β=.075, P<.001). Similarly, in model 3, the coefficients for lnP_{it} are positive and significant (β=.062, P<.001), as well as in model 4 (β=.124, P<.001). These results support hypotheses H1a and H1b.

Table 5: Regression results of main effect

Variable	Model 1 (R^2=0.193)		Model 2 (R^2=0.196)		Model 3 (R^2=0.223)		Model 4 (R^2=0.236))	
	ln$ConVol_{it+1}$		ln$ConVol_{it+1}$		ln$ConVol_{it+1}$		ln$ConVol_{it+1}$	
	β	P value	β	P value	β	P value	β	P value
Control variables								
$Title_{it}$	-0.007	.59	-0.007	.59	-0.007	.57	-0.006	.59
Off_{it}	0.001	.80	0.001	.81	-0.000	.94	0.000	.99
$Rating_{it}$	-0.003	.66	-0.001	.79	-0.008	.14	-0.004	.45
$Access_{it}$	0.000	.92	-0.000	.99	0.000	.65	0.000	.91
$HosLev_{it}$	omitted		omitted		omitted		omitted	
$Price_{it}$	-0.000	.30	-0.000	.35	-0.001	.06	-0.001	.11
Independent variables								
ln$ArtNum_{it}$	N/A[a]		0.020	.008	N/A		0.075	<.001
lnP_{it}	N/A		N/A		0.062	<.001	0.124	<.001

[a]N/A: Not applicable.

Results of the mediating effect

Table 6 demonstrates that physicians' online popularity partly mediates the effect of prosocial behavior on consultation volume. Model 5 and model 6 investigate the impact of quantity and quality of prosocial behavior on the number of followers. Compared to model 5, the results of model 6 indicate that the coefficients for ln$ArtNum_{it}$ (β=.083, P<.001) and lnP_{it} (β=.148, P<.001) are positive and significant. Furthermore, in model 7, we introduce the number of followers of popular science column, and the result reveal that the coefficients for ln$ArtNum_{it}$ (β=.032, P=.001), lnP_{it} (β=.034, P=.02), ln$Follower_{it}$ (β=.555, P<.001) are all positive and significant. Following the guidance of Wen and Ye (2014), we can conclude that physicians' online popularity plays a partially mediating role between the strength (quantity and quality) of prosocial behavior and online consultation volume. Therefore, H2a and H2b are confirmed.

Table 6: Regression results of mediating effect of physicians' online popularity

Variable	Model 5 (R^2=0.269)		Model 6 (R^2=0.334)		Model 7 (R^2=0.606)	
	ln$Follower_{it+1}$		ln$Follower_{it+1}$		ln$ConVol_{it+1}$	
	β	P value	β	P value	β	P value
Control variables						
$Title_{it}$	-0.011	.52	-0.011	.47	-0.001	.92
Off_{it}	0.003	.57	0.002	.72	-0.001	.65
$Rating_{it}$	-0.005	.51	-0.004	.54	-0.003	.48
$Access_{it}$	0.000	.16	0.000	.21	-0.000	.27
$HosLev_{it}$	omitted		omitted		omitted	
.$Price_{it}$	0.000	.56	0.000	.80	-0.001	.005
Independent variables						
ln$ArtNum_{it}$	N/A[a]		0.083	<.001	0.032	.001
lnP_{it}	N/A		0.148	<.001	0.034	.02
ln$Follower_{it}$	N/A		N/A		0.555	<.001

[a]N/A: Not applicable.

Robustness checks

We conducted three different methods to test the robustness of our findings.

Replacement of measurement indicators

First, we employed the strategy of changing measurement indicators to test the robustness. We replaced the mediating variable online popularity (*Pop*) with the number of virtual gifts (*Gifts*), and the control variable consultation price (*Price*) with the written consultation price (*WPrice*). In Table 7, we investigated the mediating role of the number of virtual gifts between prosocial behavior and online consultation. The results are consistent with our main results.

Table 7: Robustness check I using alternative measurement indicators of online popularity and consultation price

Variable	Model 8 (R^2=0.106)		Model 9 (R^2=0.223)		Model 10 (R^2=0.091)		Model 11 (R^2=0.263)	
	$lnConVol_{it+1}$		$lnConVol_{it+1}$		$lnGift_{it+1}$		$lnConVol_{it+1}$	
	β	*P* value	*β*	*P* value	*β*	*P* value	*β*	*P* value
Control variables								
$Title_{it}$	-0.007	.70	-0.006	.63	-0.007	.64	-0.004	.69
Off_{it}	0.004	.47	-0.000	.99	0.002	.69	0.001	.78
$Rating_{it}$	0.002	.79	-0.005	.30	-0.001	.86	-0.005	.30
$Access_{it}$	0.000	.90	0.000	.77	0.000	.84	0.000	.83
$HosLev_{it}$	-0.011	.63	-0.009	.49	-0.007	.72	-0.008	.54
$WPrice_{it}$	0.000	.89	-0.000	.89	-0.000	.65	-0.000	.91
Independent variables								
$lnArtNum_{it}$	N/A[a]		0.081^{***}	<.001	0.112^{***}	<.001	0.059^{***}	<.001
lnP_{it}	N/A		0.120^{***}	<.001	0.162^{***}	<.001	0.086^{***}	<.001
$lnGift_{it}$	N/A		N/A		N/A		0.174^{***}	<.001

[a]N/A: Not applicable.

Replacement of regression model with Poisson regression

In the main analysis, we used fixed-effect model to test the proposed relationships. To further test the robustness, we replaced the regression model with Poisson regression. In Poisson regression, the dependent variable should be a non-negative counting variable (Hu et al., 2021). Therefore, we replaced the independent variables with their original values instead of the logarithmic form. Table 8 shows that the hierarchical regression results are consistent with our main findings.

Table 8: Robustness check II using Poisson regression[a]

Variable	Model 12		Model 13		Model 14		Model 15	
	$ConVol_{it+1}$		$ConVol_{it+1}$		$Follower_{it+1}$		$ConVol_{it+1}$	
	β	*P* value	*β*	*P* value	*β*	*P* value	*β*	*P* value
Control variables								
$Title_{it}$	-0.004	.83	-0.004	.85	-0.008	.72	-0.002	.94
Off_{it}	0.001	.78	0.000	.94	-0.002	.75	0.001	.86
$Rating_{it}$	-0.008^{*}	.07	-0.007	.12	-0.005	.42	-0.007	.18
$Access_{it}$	0.000	.65	0.000	.54	0.000	.01	-0.000	.85
$HosLev_{it}$	omitted		omitted		omitted		omitted	
$.Price_{it}$	0.000	.14	0.000	.95	0.001	.03	-0.000	.23
Independent variables								
$lnArtNum_{it}$	N/A[b]		0.052	.001	0.069	<.001	0.040	.01
lnP_{it}	N/A		0.113	.007	0.105	.04	0.073	.08
$lnFollower_{it}$	N/A		N/A		N/A		0.282	<.001

[a]*P*<.10 at 90% CI is considered to be significant.

[b]N/A: Not applicable.

Replacement of research sample with lung cancer physicians

To further ensure the robustness of our results, we replaced the research sample with lung cancer physicians. Both Hepatitis B and lung cancer require regular and repeated online consultation, but they differ in seriousness (Yang et al., 2019). We collected a six-stage panel data set every half-month, including 1052 lung cancer physicians and 6000 observations. The results are presented in Table 9, which are consistent with our main findings. Therefore, we are confident in the robustness of our results.

Table 9: Robustness check III regression results for lung cancer physicians

Variable	Model 16 (R^2=0.257)		Model 17 (R^2=0.388)		Model 18 (R^2=0.216)		Model 19 (R^2=0.519)	
	$lnConVol_{it+1}$		$lnConVol_{it+1}$		$lnFollower_{it+1}$		$lnConVol_{it+1}$	
	β	*P* value	*β*	*P* value	*β*	*P* value	*β*	*P* value
Control variables								
$Title_{it}$	-0.022	.21	-0.019	.29	-0.020	.55	-0.013	.40
Off_{it}	0.013	.08	0.011	.07	0.017	.12	0.008	.12
$Rating_{it}$	0.050	<.001	0.041	<.001	0.043	.006	0.029	<.001
$Access_{it}$	0.000	.53	0.000	.42	0.000	.88	0.000	.41
$oHosLev_{it}$	0.000		0.000		0.000		0.000	
$Price_{it}$	-0.001	.06	-0.001	.051	-0.001	.26	-0.000	.097
Independent variables								
$lnArtNum_{it}$	N/A[a]		0.023	<.001	0.028	.007	0.017	<.001
lnP_{it}	N/A		0.023	<.001	0.046	<.001	0.044	<.001
$lnFollower_{it}$	N/A		N/A		N/A		0.273	<.001

[a]N/A: Not applicable.

Endogeneity test

There may be a positive reverse effect of prosocial behavior on physicians' online consultation. The existence of such endogeneity would bias our results (Wu and Lu, 2018). Therefore, we used two methods to address this potential issue.

Endogeneity test using lagged two-stage values

First, we further used the lagged two-stage value of independent variables and control variables in the endogeneity test. The results are shown in Table 10, which support our hypotheses.

Table 10: Endogeneity test Ⅰ using lagged two stage value[a]

Variable	Model 20 (R^2=0.199)		Model 21 (R^2=0.217)		Model 22 (R^2=0.320)		Model 23 (R^2=0.468)	
	$lnConVol_{it+2}$		$lnConVol_{it+2}$		$lnFollower_{it+2}$		$lnConVol_{it+2}$	
	β	*P* value	*β*	*P* value	*β*	*P* value	*β*	*P* value
Control variables								
$Title_{it}$	-0.005	.65	-0.005	.67	-0.008	.56	-0.001	.90
Off_{it}	0.002	.57	0.002	.58	0.005	.32	0.001	.87
$Rating_{it}$	-0.010	.08	-0.010	.097	-0.011	.11	-0.007	.16
$Access_{it}$	0.000	.99	-0.000	.97	0.000	.38	-0.000	.42
$HosLev_{it}$	omitted		omitted		omitted		omitted	
$.Price_{it}$	-0.000	.36	-0.000	.20	-0.000	.76	-0.001	.08
Independent variables								
$lnArtNum_{it}$	N/A[b]		0.063	<.001	0.070	.001	0.040	.005
lnP_{it}	N/A		0.103	<.001	0.115	<.001	0.035	.06
$lnFollower_{it}$	N/A		N/A		N/A		0.431	<.001

[a]*P*<.10 at 90% CI is considered to be significant.

[b]N/A: Not applicable.

Endogeneity test using instrumental variable estimation approach

In addition, we employed a two-stage least squares (2SLS) method to identify the endogeneity of the quantity of physicians' prosocial behavior. On Haodf.com, physicians have the option to upload personal photos and display a standard profile image if they do not provide a picture (Ouyang and Wang, 2022). Physicians who choose to upload personal images may do so to convey friendliness and kindness to patients. Generally, this could lead to increased engagement in prosocial behavior and, consequently, resulting in more consultations. Furthermore, uploading personal image has nothing to do with professional skills and service attitudes, so it is less likely to impact online consultation volume. Taking these factors into account, we used a dummy variable indicating whether a physician has personal image ("1" for yes and "0" for no) as the instrumental variable for measuring the quantity of prosocial behavior.

From Table 11, we can see that the coefficient of *Image* (β=.967, p<.001) is positive and significant at the first-stage, and the coefficient of ln*ArtNum* (β=1.229, p<.001) is also positive and significant at the second-stage, aligning with our main results. Additionally, the Cragg-Donald Wald F statistic (242.57) exceeded the critical value of the Stock-Yogo weak instrumental variable recognition F test at the 10% significance level (16.38), indicating the absence of weak instrument problem (Wu and Lu, 2018).

Based on the results of the endogeneity test, we can confidently assert the validity of our findings.

Table 11: Endogeneity test Ⅱ using 2SLS estimation

Variable	Model 24 First-stage (R^2=0.305)		Model 25 Second-stage (R^2=0.159)	
	lnArtNum		lnConVol	
	β	*P* value	β	*P* value
Control variables				
Title	0.292	<.001	0.036	.54
Off	0.249	<.001	0.140	.02
Rating	0.986	<.001	0.344	.002
Access	0.000	<.001	-0.000	.02
HosLev	-0.216	.07	-0.050	.72
Price	0.004	.01	0.010	<.001
Independent variables				
Image	0.967	<.001	N/A	
lnArtNum	N/A[a]		1.229	<.001
Cragg-Donald Wald F statistic			242.57 [16.38][b]	

[a]N/A: Not applicable.

[b]Notes: Value in brackets is the critical value of the Stock-Yogo weak instrumental variable recognition F test at the 10% significance level.

DISCUSSION

Findings

While there has been extensive research on the influence of physicians' online returns, only a few studies have examined the impact of physicians' prosocial behavior on consultation volume in the context of OHC. To address this research gap, we conducted a study using a large secondary dataset of 1,015 physicians on Haodf.com, the largest OHC in China. Drawing on information asymmetry theory, signaling theory and reciprocity theory, we established an empirical model and tested four proposed research hypotheses. Our findings, supported by empirical regression, shed light on the impact of physicians' prosocial behavior on consultation volume, specifically from the perspective of follower interaction for the first time.

Our study reveals three significant findings. Firstly, the strength of physicians' prosocial behavior can positively influence online consultation. By performing prosocial behavior, physicians demonstrate their professional skills and service attitudes, which improves patients' consultation decision belatedly owing to reciprocity principle. Secondly, physicians' online popularity partially mediated this promotion effect. On the one hand, physicians can accumulate online popularity through high strength of prosocial behavior in personal popular science column. On the other hand, patients tend to choose physicians with high online popularity for consultation., as online popularity serves as a signal perceived by subsequent patients, influenced by the bandwagon heuristic (Sundar, 2008). Our empirical results confirm that physicians' online popularity plays a partially mediating role between their prosocial behavior and online consultation volume. Lastly, these findings can be applied to chronic diseases of varying severity. The promotion effect of physicians' prosocial behavior on their online consultation volume is consist with the research of Wang (Wang et al., 2022), and through the mediating effect of online popularity, we further clarify the influencing mechanism from the perspective of fan interaction for the first time.

In summary, our study fills a research gap by examining the impact of physicians' prosocial behavior on consultation volume in the context of OHC. The results highlight the positive influence of physicians' prosocial behavior on consultation volume and the mediating role of online popularity. These findings have implications for understanding and improving healthcare services, particularly for chronic diseases.

Theoretical implications

Theoretical implications of this study can be categorized into four main aspects.

Firstly, this study is the first attempt to empirically demonstrate the impact of physicians' prosocial behavior on consultation volume from the perspective of fan interaction. Previous literature has examined the relationship between prosocial behavior and consultation volume from the physicians' perspective, such as professional title and online ratings. However, in the current study, we provide empirical evidence that both the number of followers of popular science column and the number of virtual gifts can partially mediate the promotion effect.

Secondly, this study contributes to the literature on prosocial behavior in the context of OHC, which is relatively unexplored area. While previous studies have predominantly examined prosocial behavior in offline markets (Ariely et al., 2007; Exley, 2018; Lacetera and Macis, 2010), whereas little research has examined it in online health community, this study enriches the understanding of prosocial behavior in the form of health articles and videos, free live diagnoses.

Thirdly, our research adds to the existing literature on online information sharing. Although the antecedents (i.e. the motivation) of online information sharing have been extensively studied (Jing et al., 2019; Qi et al., 2021; Yang et al., 2021; Zhou et al., 2020), few studies look at the utility of medical science knowledge sharing. Our findings reveal that physicians not only increase online returns, but also enhance their online popularity (followers and virtual gifts) through sharing online information.

Finally, this study enriches the literature on factors that can influence physicians' online performance. While previous studies have focused on physicians' personal characteristics (Li et al., 2019; Yang et al., 2020a) and patient-generated information (Deng et al., 2019; Peng et al., 2020), our study highlights the effect of online effort on consultation volume.

Practical implications

The findings have practical implications for participants in OHC: physicians, managers, and patients.

This study highlights the facilitating role of prosocial behavior on consultation volume. It suggests that physicians may be motivated to dedicate more time and effort to performing prosocial behavior in order to cultivate a warm and caring image and unconsciously increase their online income.

For platform managers, this paper suggests taking measures to encourage physicians to engage in prosocial behavior. One approach could be designing the website layout to prompt more patients to send virtual gifts. Additionally, managers should consider enhancing the importance of physician's popular science column module to ensure the continued success of OHC.

Our findings of this study also have realistic implications for patients. By observing physicians' prosocial behavior, patients can gain a clearer understanding of physician's service attitude and area of expertise. Hence, when making online medical decisions, patients should not only consider the physicians' personal characteristics but also pay attention to their prosocial behavior in order to choose the most suitable physician. Furthermore, patients can enhance their health literacy by observing physicians' prosocial behavior, enabling them to better comprehend their disease and treatment plans.

Limitation And Future Work

This study has several limitations that should be acknowledged. First, while we selected representative physicians based on existing literature, our study only involved two departments (hepatitis B physicians and lung cancer physicians), which may introduce bias. To ensure the validity of our findings, it is necessary to cross-validated the results using data from a larger sample of physicians across various departments. Second, we paid major attention to chronic disease physicians but neglected the perspective of acute disease physicians. Given the time-sensitive nature of acute diseases, patients may not have sufficient time to explore the valuable information contained in physicians' prosocial behavior. This aspect warrants further investigation as it may lead to different conclusions. Third, our observations were limited to Chinese physicians, and it is important to recognize that the influential mechanism may be different from other countries due to cultural variations. Future research may address the issue through incorporating cross-platform datasets to compare and contrast findings across different cultural contexts. Finally, we measured the quality of prosocial behavior using *P*-value, which aligns with the peripheral path of thinking according to the elaboration model (ELM) (Petty and Cacioppo, 1984). To enhance the persuasiveness of our findings, it would be beneficial to employ text analysis technique to assess the quality of prosocial behavior through the central path of thinking.

CONCLUSIONS

This study aimed to investigate the impact of physicians' prosocial behavior consultation volume within in an OHC. Drawing on information asymmetry theory, signaling theory and reciprocity theory, we developed an empirical model and examined its effects using secondary data. The results demonstrated a positive relationship between physicians' prosocial behavior and consultation volume. Furthermore, we found that this effect was partially mediated by physicians' online community. Our research is the first literature that sheds lights on the impact of physicians' prosocial behavior on consultation volume from follower interaction. Our findings have some practical implications for physicians, platform managers and patients. However, it is crucial to acknowledge the limitations of this study, which call for further research attention on physician's prosocial behavior in OHC.

AUTHOR'S CONTRIBUTION

MAO conceived the idea, designed the project and wrote the manuscript. ALHASSAN performed the data collection and statistical analysis. HUANG participated in the design of the study and helped in writing the manuscript. All authors read and approved the final manuscript.

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