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Understanding the factors influencing health professionals' online voluntary behaviors: Evidence from YiXinLi, a Chinese online health community for mental health

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ABSTRACT

Background: Normal users' voluntary behaviors (e.g., knowledge sharing) in virtual communities (VCs) has been well investigated; however, research on health professionals' voluntary behaviors in online health communities (OHCs) is limited.

Objective: This paper focuses on OHCs for mental health and aims to explore how intrinsic and extrinsic motivations influence mental health service providers' voluntary behaviors.

Methods: Based on motivation theory and prior studies, we incorporated technical competence as intrinsic motivation and online reputation and economic rewards as extrinsic motivations, and proposed five hypotheses. We crawled objective data from YiXinLi, a Chinese OHC for mental health, and tested the hypotheses based on the Poisson regression model. All hypotheses are supported.

Results: 1) Technical competence, online reputation, and economic rewards positively influence mental health service providers' voluntary behaviors; 2) the interaction effect between technical competence and online reputation negatively influences mental health service providers' voluntary behaviors; 3) the interaction effect between technical competence and economic rewards negatively influences mental health service providers' voluntary behaviors.

Conclusions: Both intrinsic motivations and extrinsic motivations positively influence mental health service providers' voluntary behaviors, and their interaction effects negatively influence mental health service providers' voluntary behaviors. This study first contributes to the literature on health professionals' voluntary behaviors in OHCs by verifying the positive effect of economic rewards. It then contributes to motivation theory by incorporating a situation where intrinsic motivations and extrinsic motivations could negatively interact.

1. Introduction

With the development of Web 2.0 technologies, online health communities (OHCs) have become increasingly popular. Different types of OHCs are built for different purposes. For example, some OHCs are built as communities of practice for health practitioners to conduct peer interaction and learn from each other [1–5], some are built only for normal users, such as patients and their relatives, who use them for peer support [6–9], while others are built as platforms that link health professionals and normal users to conduct health-related activities [10–12]. This paper focuses on the last type. In open OHCs, health professionals can input their professional knowledge into OHCs through different online activities (e.g., writing professional articles, responding to normal users' questions, and/or providing chargeable health services), while normal users can ask for medical or clinical suggestions via the online Q&A systems and/or pay money to make appointments with health professionals.

OHCs have recently been used to support mental health. Mental health illness is a severe issue both in China and other countries and affects one in six worldwide [13]. Because mental health illness is strongly stigmatized [14,15], individuals who have a mental illness sometimes deny to see a mental health service provider or delay to seek help, causing negative health outcomes [14–17]. Unlike other diseases that rely on physical treatments, many problems related to mental health could be alleviated via counseling. This makes online counseling (e.g., written texts, email, telephone, and/or video counseling) an

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effective way to alleviate issues related to mental health [18–20]. OHCs for mental health act as intermediaries by linking mental health service providers[1] with individuals who have mental health conditions (hereafter referred to as normal users), and they have become increasingly popular.

Health professionals are the providers of health-related information and services in OHCs; however, current studies mainly focus on the receivers of health information and services. For example, many studies focus on the patients' OHC use and explore their related behaviors, such as informational/emotional support exchange, privacy disclosure, and privacy protection in OHCs [7,21,22,9,23–26]. While it is imperative to examine the normal users' OHC use, health professionals' participatory behaviors are also crucial to the sustainability of OHCs [27,28]. Health professionals provide credentialed health information in OHCs, and their authority ensures the knowledge quality in OHCs [29,12]. However, there is a paucity of studies on health professionals' participatory behaviors in OHCs, and scholars should pay more attention to these behaviors [10,30,31].

Health professionals' participatory behaviors in OHCs could be categorized into chargeable ones and voluntary ones. The chargeable ones refer to behaviors like providing chargeable consulting services [10,18,32]. The voluntary ones refer to activities like freely sharing knowledge or answering normal users' online questions in OHCs [28,31,33]. Considering that the number of online free-chasing users is overwhelmingly more than users who are willing to pay money [34], examining the factors influencing health professionals' voluntary behaviors can help us better understand how to motivate health professionals to provide more free online health services and meet those free-chasing users' needs.

Existing research mainly focuses on the factors influencing health professionals' chargeable behaviors; however, not much research has been done on the factors that influence health professionals' voluntary behaviors. Some studies have explored the effects of social incentives and economic rewards on doctors' online appointments (i.e., chargeable behaviors) ([11,35,36,12]) or numbers of patients [37]. Although some scholars have explored health professionals' voluntary behaviors (e.g., knowledge sharing) in VCs [31], they mainly focus on the effects of intangible factors (e.g., altruism, knowledge self-efficacy, reputation, and reciprocity), but do not investigate the influence of tangible factors (e.g., economic rewards). Although health professionals are social work professionals, they also face severe professional burnout and need economic rewards [38,39]. The effects of economic rewards should be incorporated. In addition, although some studies have addressed the relationships between intrinsic and extrinsic motivations and how their interaction affects individuals' behaviors, their conclusions are inconsistent [37,40]. Thus, this paper aims to systematically investigate the factors influencing health professionals' voluntary behaviors. We focus on mental health service providers' voluntary behaviors in OHCs for mental health and try to answer the following question:

How do intrinsic motivations and extrinsic motivations influence mental health service providers' voluntary behaviors in OHCs for mental health?

Based on motivation theory and prior research, we built a hypothesis model with five hypotheses and crawl objective data from an OHC for mental health to test the model. The empirical results show that intrinsic motivations and extrinsic motivations not only directly influence but also interact with each other and exert negative effects on mental health service providers' voluntary behaviors. This study makes two significant contributions. First, we contribute to the literature on health professionals' voluntary behaviors in OHCs by incorporating the effects of economic rewards. Second, we contribute to motivation theory by verifying a situation where intrinsic motivations and extrinsic motivations could negatively interact.

The rest of this paper is organized as follows. We first introduce the theoretical foundation and hypotheses development and then present the methodology including data collection and data analysis. In the following part, we discuss theoretical contributions, practical implications, and limitations. The last section is the conclusion.

2. Theoretical foundation and hypotheses

2.1. Motivation theory

We adopt motivation theory as our theoretical foundation. Motivation theory proposes that individuals' behaviors are driven by certain motivations, e.g., intrinsic and extrinsic motivations [41]. Intrinsic motivation refers to doing something because it is inherently interesting or enjoyable, while extrinsic motivation refers to doing something because it leads to a separable outcome [41]. Motivation theory is widely applied to explain individuals' online behaviors, e.g., knowledge sharing behaviors in virtual communities (VCs) [42–45].

Motivation theory has recently been used to explain individuals' health-related behaviors in OHCs [10,24,31]. For example, compared with normal users who are mainly driven by reciprocity, altruism, and empathy, health professionals are mainly driven by self-efficacy and reputation when sharing knowledge in OHCs [31]. Although doctors are social work professionals and are mainly driven by social incentives, they also need economic rewards [10]. The above evidence indicates that motivation theory is appropriate to explain health professionals' voluntary behaviors in OHCs.

2.2. Motivational factors in VCs or OHCs studies

In order to better understand the effects of motivational factors on health professionals' voluntary behaviors in OHCs, we review the relevant studies in the context of VCs or OHCs and present the related information in Table 1.

We gain several insights from Table 1. First, health professionals' competence should be incorporated into consideration. An individual's capability is usually treated as intrinsic motivation and is important in driving online behaviors. Scholars have addressed this requirement by adopting self-efficacy or knowledge self-efficacy in a VC context [31,40,47], or doctors' professionals titles [36] or professional seniority [37] in an OHC context. Second, economic rewards are seldom investigated and should be incorporated. Although scholars have examined the effects of extrinsic motivations, they usually examine factors such as reputation and/or reciprocity (see the last row in Table 1). Considering that health professionals could obtain economic rewards in OHCs [10] and face severe professional burnout [39], the effects of economic rewards should be incorporated. Third, there are inconsistent findings in prior studies. For example, some scholars propose that extrinsic motivations moderate the effects of intrinsic motivations [40], while others propose that intrinsic motivations moderate the effects of extrinsic motivation [37]. The relationships between extrinsic motivations and intrinsic motivations should be further examined.

Although reciprocity is mentioned in prior research on OHCs [31] and VCs [40,44], we do not include it in our model. We have two reasons for doing this. First, the positions of health professionals and normal users in OHCs are different. Health professionals usually have more professional knowledge than normal users [48]. The help in OHCs between health professionals and normal users is usually a one-direction trip (i.e., from health professionals to normal users). It is difficult for health professionals to get insightful answers from normal users. Second, economic rewards as direct returns are usually more crucial than uncertain returns in the future (e.g., reciprocity). Many health professionals face severe professional burnout and need economic rewards [39]. They participate in OHCs in order to get economic returns.

[1] Note: hereafter we use "health professionals" as a general concept that includes all types of health professionals, and we use "mental health service providers" to refer to health professionals for mental health.

Table 1
Users' participatory behaviors in VCs or OHCs.

References	Contexts	Objects	Dependent variable(s)	Motivational factors		
				Intrinsic factors		Extrinsic factors
[44]	Electronic networks of practice	Normal users	Helpfulness of knowledge	Enjoy helping (ns)		Reputation (+), Reciprocity (ns)
			Volume of knowledge	Enjoy helping (ns)		Reputation (+), Reciprocity (-)
[46]	VCs	Normal users	Information sharing behavior	Intrinsic motivation (+)		Extrinsic motivation (ns)
[47]	VCs	Normal users	Quantity of knowledge	Enjoy helping (+), Knowledge self-efficacy (+), Self-worth (+)		Reward in reputation (+)
			Quality of knowledge	Enjoy helping (+), Knowledge self-efficacy (+), Self-worth (+)		Reward in reputation (ns)
[45]	Outsourcing VCs	Normal users	Participation effort	Intrinsic motivation (+)		Integrated motivation (ns), Identified motivation (ns), Introjected motivation (+), External motivation (+)
[40]	Social Q&A sites	Normal users	Attitude towards knowledge sharing	Enjoyment in helping others (+)	Self-efficacy (+)	Organizational rewards (-, moderating) Reciprocity (-, moderating)
[24]	OHCs	Normal users	Knowledge sharing	Sense of self-worth (+)		Reputation (+), Social support (+)
[36]	OHCs	Health professionals	Online appointments	Personal offline reputation (titles, +)		Personal online reputation (positive feedbacks, +)
[31]	OHCs	Normal users	Knowledge sharing behaviors	Knowledge self-efficacy (ns), Altruism (+), Empathy (+)		Reputation (-), Reciprocity (+)
		Health professionals		Knowledge self-efficacy (+), Altruism (+), Empathy (ns)		Reputation (+), Reciprocity (+)
[37]	OHCs	Health professionals	Numbers of patients	Professional seniority (-, moderating)		Online rating (+)

Fig. 1. Hypotheses and research model.

In such a situation, the effect of reciprocity might not be important.

2.3. Research model and hypotheses

Based on the above evidence, this paper incorporates three motivational factors and explores their effects on mental health service providers' voluntary behaviors in OHCs for mental health. Specifically, we use technical competence to describe the mental health service providers' professional capabilities and treat it as intrinsic motivation, adopt online reputation and economic rewards as extrinsic motivations, and build the research model (see Fig. 1).

2.3.1. Direct effects

Technical competence in this paper refers to a mental health service provider's professional capability in performing the necessary professional tasks [49]. Individuals need appropriate capability in conducting some activities. For example, both normal users and health professionals need knowledge self-efficacy in conducting knowledge sharing behaviors in VCs [31,40,47]. For mental health service providers, their professional capabilities are crucial in driving them to provide professional services. Scholars have addressed this and adopted the numbers of professional titles or title rank to estimate health professionals' technical competence; those who have higher levels of technical competence could conduct more health-related behaviors [11,36,37,12]. Specific to this paper, we propose that mental health service providers also need technical competence to conduct voluntary behaviors and hypothesize that

H1. Technical competence positively motivates mental health service providers to conduct voluntary behaviors in OHCs for mental health

Online reputation in this paper refers to the Internet-based individual rating of mental health service providers in OHCs for mental health [50]. The advancement of information and communication technologies makes online reputational signals such as electronic word of mouth (i.e., eWoM) and user-generated rating services become ubiquitous. Online reputation such as positive online feedback provides necessary information on a health professional's performance [50,51]. On the one hand, in order to build reputation in OHCs, health professionals can participate in different activities (e.g., Q&As or chargeable services) [10–12] and share different types of health knowledge with others [52]. Namely, online reputation acting as extrinsic motivation drives individuals to share knowledge in VCs or OHCs [24,36]. On the other hand, those health professionals with good reputations have pressure to keep their positive profiles and choose to share knowledge through answering normal users' questions. We thus hypothesize that

H2. Online reputation positively motivates mental health service providers to conduct voluntary behaviors in OHCs for mental health

Health professionals are also self-interested and need tangible rewards [38]. However, doctors in China are usually treated as professional social workers and should not be oriented by economic rewards [10]. In addition, they have to intensively work on treatments due to a lack of health professionals in China. Many doctors thus experience occupational burnout and need economic rewards to compensate for their professional stress [39]. OHCs offer health professionals in China an opportunity to earn money online. Health professionals could join OHCs and be recognized as experts and then provide chargeable health services to individuals who are willing to pay money [10–12]. For example, in OHCs for mental health, mental health service providers could provide chargeable counseling via telephone, video, and/or face-to-face services [14,18,11,15,12]. In China, there are increasingly more patients that have adopted OHCs and choose to make appointments with mental health service providers online [11,12]. The economic rewards that mental health service providers earn via those chargeable behaviors online could compensate for their professional burnout and encourage them to voluntarily interact with normal users in OHCs. We thus hypothesize that

H3. The economic rewards positively motivate mental health service providers to conduct voluntary behaviors in OHCs for mental health

2.3.2. Interaction effects

The effects of intrinsic motivations and extrinsic motivations on users' participation behaviors have been well investigated in prior studies (see Table 1); however, the interaction effects between intrinsic motivations and extrinsic motivations remain underexplored [37,40]. Some scholars have noticed this issue and tried to address it. For example, intrinsic motivations and extrinsic motivations together may not complement individuals' behaviors [53]. Extrinsic motivations could undermine the positive effects of intrinsic motivation through two interrelated psychological processes (i.e., diminished self-determination and impaired self-esteem) [53]. This phenomenon has been verified in social Q&A sites, e.g., virtual organizational rewards as extrinsic motivation undermines the effects of enjoyment in helping others on attitudes toward knowledge sharing, while reciprocity as extrinsic motivation undermines the effects of knowledge self-efficacy on attitudes toward knowledge sharing [40]. Another study in the context of OHCs has also verified the substitutive effects; however, they find that professional seniority as an intrinsic motivation negatively moderates the effects of two extrinsic motivational factors (i.e., online rating and a doctor's activeness) [37]. There is significant inconsistency on the relationships between intrinsic motivations and extrinsic motivations in prior studies [37,40]. In order to address the above inconsistency, this paper proposes a negative interaction effect between intrinsic motivations and extrinsic motivations.

In this paper, we propose that the negative interaction effects between intrinsic motivations and extrinsic motivations also exist in the context of OHCs for mental health. They interact with each other and negatively influence mental health service providers' voluntary behaviors. The above proposition is based on two pieces of evidence. First, normal users usually like to make appointments with mental health service providers who have higher levels of technical competence. Second, normal users can review a mental health service provider only after the chargeable counseling is done. Namely, higher levels of online reputation or economic rewards means a mental health service provider has completed a higher volume of chargeable services and thus has shown limited efforts to do other activities including voluntary behaviors. Therefore, when both technical competence and online reputation (or economic rewards) are high, mental health service providers become popular and will have limited time to do voluntary behaviors; thus, the volume of voluntary behaviors will be low. When both technical competence and online reputation (or economic rewards) are low, mental health service providers might not be popular and will have fewer online appointments; they thus have more time to do voluntary behaviors, so the volume of voluntary behaviors will be high. When either one of them (i.e., technical competence and online reputation/economic rewards) is high, the volume of voluntary behaviors will be at a medium level. We thus hypothesize that

H4. The interaction effect between technical competence and online reputation negatively influences mental health service providers' voluntary behaviors in OHCs for mental health.

H5. The interaction effect between technical competence and economic rewards negatively influences mental health service providers' voluntary behaviors in OHCs for mental health.

Men and women might act differently in voluntary knowledge sharing [54,55], and we treat gender as a control variable. Mental health service providers' education and prior professional practice might influence their professional performance [56], and we treat education and practical experience (i.e., how long they have provided professional service) as two other control variables. As the time when they became a member of OHC passes, different professional knowledge providers might split into lurkers and posters [57]; namely, their behaviors might be related to time on website. We treat time on website as a control variable. In addition, OHCs can change information inequalities by transferring health information from urban users to users in small cities or rural areas [6,58]; therefore, the city where a provider lives might exert its influence. We treat city as another control variable.

3. Methods

3.1. Data collection

We selected *YiXinLi* (www.xinli001.com), a Chinese OHC for mental health, as our data sampling community. The reasons are as following. First, *YiXinLi* is a pioneer in the online mental health service market. Mental health is strongly stigmatized in China. Mental health service has long been a low priority in China due to various reasons [59]. *YiXinLi,* set up by several mental health service providers in 2011, aims to promote mental health service practice in China via the Internet. Their effort was recognized by the capital and the public. The website already obtained four rounds of venture investment and earned 22 million registered users as of May 2019. Second, *YiXinLi* supports mental health service providers with both chargeable behaviors and voluntary behaviors. *YiXinLi* does not have its own mental health service providers. It just acts as a platform that links mental health service providers and normal users, which meets the research aim in this paper. Third, the mental health service providers are more experienced than the counselors on some other websites. We extracted a new variable named practical experience to describe how long a provider has provided mental health service. Although practical experience ranges from one year to thirty-one years, there are only two providers who have one year of experience and six providers who have two years of experience as of the end of 2017, and more than 97% providers have more than two years of practical experience. We checked two other websites that provide similar services and found that they allow junior counselors (e.g., some are still undergraduate students) to independently provide counseling services online. Holding a strict criterion on mental health service providers is a significant difference between *YiXinLi* and some other websites.

On *YiXinLi*, users can ask questions and wait for free answers via the Function Q&As platform (see Fig. 2). The answers can be provided by other users or mental health service providers. For mental health service providers, answering questions is free and belongs to voluntary behaviors. Users can also make appointments with mental health service providers and seek chargeable services via the Function Counseling platform (see the green "pro" in Fig. 2; it means counseling can only be provided by recognized professional mental health service providers). For mental health service providers, responding to chargeable online

Fig. 2. Sample Page of a *YiXinLi* Q&A System.

appointments belongs to chargeable behaviors and could bring them economic rewards.

Mental health service providers on *YiXinLi* are recognized under various strict criteria. First, mental health service providers apply to be recognized via offline channels. They should provide copies of their education background and professional training experience. If those materials meet the related criteria, there will be an interview. Second, mental health service providers will be interviewed by three officers. They will be independently evaluated by the three officers on their education, technical skills, and professional ethics. If they pass, they will receive an account and can create their own personal home page on *YiXinLi* (see Fig. 3). The website automatically records all information related to a mental health service provider.

We got permission from *YiXinLi* and crawled data separately in September and December 2017. We matched the mental health service providers' personal information and built a two-period balanced panel data (with 230 health professionals in each period).

3.2. Variables and measurement

We conceptualized seven variables and operationalized them using seven measures (see Table 2). The dependent variable *voluntary behavior* is measured with the mental health service providers' voluntary responsiveness to user questions on *YiXinLi*. The detailed measurement of all variables is shown in Table 2.

3.3. Data analysis

Table 3 shows the descriptive statistics and correlations between different variables. There are 62 male mental health service providers (27.0%) and 168 mental health service providers (73%). There are 167 (63%), 33 (14.0%), and 30 (13.0%) mental health service providers respectively working in first-tier cities, second-tier cities, and others.

Considering that the dependent variable *voluntary behavior* varies from 0 to 11189 and overdispersion has occurred, we follow the econometric modeling guidelines [67] and studies in IS literature [68] and adopt the Poisson regression model to test the hypotheses. Because we have a two-period-balanced dataset, we run the *poisson* model with the *vce (cluster panel-id) nolog* option. The standard Poisson regression model is jointly defined by equations 1 and 2. Before doing the regression, we standardized all the independent variables.

Fig. 3. Sample of a Health Professional's Homepage.

Table 2
Variables and measurements.

Variables	Measurements
Voluntary behavior (VB)	We use the volume of voluntary responsiveness to user questions to measure a mental health service provider's voluntary behavior. For example, the mental health service provider in Fig. 2 has completed 7 answers, and the value of voluntary behavior is 7.
Technical competence (TC)	We used the number of professional titles that a mental health service provider has to measure his/her capability. The 230 service providers hold 308 different professional titles. These titles were used 453 times. We categorized these titles into six types. Specifically, professional titles appeared in the dataset include education level (e.g., their degree, appeared 48 times), professional certification (e.g., National Counseling level 2, etc. appeared 244 times), professional training (e.g., China-U.S. joint psychology training course, etc. appeared 15 times), professional membership (e.g., APA, etc. appeared 10 times), positions (e.g., chief counselor or founder of a counseling institute, etc. appeared 132 times), and professional achievements (e.g., the top 10 counselors in 2016 by XXTV, etc. appeared four times). *YiXinLi* allows service providers to provide their titles but limits the field for professional titles to 20 Chinese characters. A service provider cannot provide their titles according to their will but has to provide limited ones – this is one reason why the mean value and variation of technical competence is low (see Table 3). Considering that detailed professional titles are various, it is difficult to compare the power of different titles. We thus use the number of titles a mental health service provider has to evaluate his/her capability. **This approach of counting the number of credentials as a measure of competence is consistent with the approach in prior research**. For example, scholars use the number of articles published, number of citations, and number of article pages to assess authors' scholarly competence or quality [60,61], or scholars use the number of negative emotion words people use to assess their mental distress [62]. Some scholars might argue whether titles like APA membership could represent a mental health service provider's competence or not. We understand the concern that titles such as APA membership don't sufficiently represent competence. However, considering the relatively low health literacy in China [63] and normal users' limited knowledge in differentiating the nature of those titles, using the number of professional titles to measure a mental health service provider's competence is reasonable. For example, the mental health service provider in Fig. 2 has two titles (i.e., master of psychology, APA member), and the value of her technical competence is 2.
Online reputation (OR)	We use the number of positive feedbacks a mental health service provider receives to measure his/her online reputation. **This approach is popularly used in prior research**. Online feedback, also known as online reviews or electronic word of mouth (e-WOM), refers to the Internet-based consumer rating of online goods or services (e.g., restaurants, hotels, or books) [50]. Positive feedback not only provides necessary information on goods or service quality [51,50], but is also an indicator of social reputation [64]. In this paper, we use the volume of positive feedbacks a mental health service provider receives as a measurement. For example, the mental health service provider in Fig. 2 has 1349 positive feedbacks, and the value of online reputation is 1349.
Economic rewards (ER)	**Economic rewards** refer to the money that a mental health service provider earns via providing chargeable services. It is measured by the interaction term ***service volume*** * ***service price***. **Service volume** : The volume of chargeable behaviors (service volume) refers to the total volume of telephone, video, and face-to-face counseling. For example, the volume of chargeable appointments in Fig. 2 is 1597, so the value of the service volume is 1597. **Service price** : *YiXinLi* allows mental health service providers to provide three kinds of counseling (i.e., telephone, video, and/or face-to-face counseling). The website doesn't record the detailed volume of each counseling. In addition, according to the coding results, service price is a time-invariant variable. We thus use the mean value as a measurement. For example, the service price value in Fig. 2 is 633 ((600 + 500 + 800)/3 ≈ 633).
Gender	Gender was coded with "0" for male and "1" for female.
Practical experience	Practical experience refers to how long a mental health service provider has provided professional service. This variable was extracted from the introduction texts on a mental health service provider's home page. We use it to describe the profiles of mental health service providers on *YiXinLi*.
Education level	Education level was extracted from the professional titles and introduction texts on a mental health service provider's home page. We first searched keywords such as "bachelor, master, and PhD" and coded the variable into "0 for no related information", "1 for bachelor", "2 for master", and "3 for PhD" according to the search results, then searched keywords such as "college or university" to further check their education experience, and finally rechecked the whole coding for education level manually.
City	City refers to the location where a mental health service provider works and was coded as a categorical variable (i.e., first-tier city, 2; second-tier city, 1; others, 0) according to the latest classification criteria [65,66]. The ranking is based on five indicators: concentration of commercial resources, city's pivotability, citizen vitality, variety of lifestyle, and flexibility in the future [65]. According to this new ranking system, there are 4 first-tier cities and 15 new first-tier cities. We include the 19 cities into first-tier cities. There are 30 second-tier cities [65].
Time on website (ToW)	Time on website refers to the amount of time since a mental health service provider joined the community. We compared the date a mental health service provider joined *YiXinLi* with the date when we collected data.

$$f(y_{it}x_{it}) = \frac{e^{-\mu_{it}}\mu_{it}^{y_{it}}}{y_i!},\ y_{it} = 0,\ 1,\ 2,\ \ldots$$

$$\mu_{it} = \exp(x_{it}^{'}\beta)$$

where:

$y_{it}|x_{it} \sim Poisson$

$\mu_{it} > 0$

y_{it} represents the count of the DV for the t^{th} observation in the i^{th} group

$\boldsymbol{x}_{it}$ represents a vector of predictors for the t^{th} observation in the i^{th} group

$\boldsymbol{\beta}$ represents a vector of parameters for the model predictors

3.4. Results

Because online reputation and economic rewards show collinearity (see Table 3), adding online reputation and economic rewards in the same model might change the significance of their effects. We thus run different models to test the effects of independent variables. Specifically, we use model 0 to test the effects of control variables; use models 1 and 2 to test hypotheses 1, 2, and 4; and use models 3 and 4 to test hypotheses 3 and 5. All the Poisson regression models are estimated with Stata 14. The final results are shown in Table 4.

As shown in Table 4, the effect of gender is significant at the 0.1 level or better. Namely male mental health service providers have conducted more voluntary behaviors than female ones. The effect of city of practice in this study is insignificant, indicating that the place a mental health service provider works does not matter, and mental health service providers from big or small cities do not show significant differences when voluntarily responding to normal user questions in OHCs. The effect of education level is insignificant, indicating education level does not directly influence a provider's voluntary behaviors. The effect of practical experience is insignificant, indicating practical experience does not directly influence a provider's voluntary behaviors. The effect of time on website is insignificant, indicating that a longer community membership does not necessarily indicate a higher volume of voluntary behaviors.

The effect of technical competence is significant in models 1 and 2. H1 is supported. Mental health service providers provide the number of their titles and want to show their capabilities or their professional trainings. Mental health service providers who have more titles are

Table 3
Descriptive statistics of mental health service providers' data (two periods).

September only, N = 230

#	Mean	SD	Min	Max	VB	TC	Edu	OR	ER	Gen	PE	City	ToW
VB	420.540	1264.897	0	10872	1								
TC	1.970	.705	1	4	.146*	1							
Edu	.96	1.065	0	3	−.038	.202**	1						
OR	48.020	143.364	0	1192	.452**	.190**	−.013	1					
ER	39980.300	102881.170	0	898975	.420**	.195**	.023	.971**	1				
Gen	.730	.445	0	1	−.112	−.050	.040	−.012	.010	1			
Ten	8.14	4.611	1	31	−.016	−.118	−.054	.005	−.002	−.115	1		
City	1.590	.704	0	2	−.107	.031	.075	−.040	−.032	−.005	−.045	1	
ToW	588.048	297.236	45	2343	.213**	−.071	−.122	.123	.132*	−.018	−.018	.074	1

December only, N = 230

#	Mean	SD	Min	Max	VB	TC	Edu	OR	ER	Gender	Ten	City	ToW
VB	446.660	1304.756	0	11189	1								
TC	1.970	.705	1	4	.149*	1							
Edu	.96	1.065	0	3	-.042	.202**	1						
OR	55.260	155.456	0	1299	.452**	.192**	-.006 −.006	1					
ER	54139.661	126937.430	0	1050750	.397**	.189**	.043	.939**	1				
Gen	.730	.445	0	1	−.116	−.050	.040	−.016	.001	1			
PE	8.14	4.611	1	31	−.017	−.118	−.054	.005	−.002	−.115	1		
City	1.600	.715	0	2	−.070	.005	.012	.012	.040	.020	.005	1	
ToW	710.048	297.236	167	2465	.219**	−.071	−.122	.126	.124	−.018	−.018	.055	1

Note: two-tail test; VB stands for voluntary behaviors, TC for technical competence, Edu for education level, OR for online reputation, ER for economic rewards, Gen for gender, PE for practical experience, ToW for time on website; *P < 0.05, ** P < 0.01.

Table 4
Results of Poisson Regression Model.

	Model 0	Model 1	Model 2		Model 3	Model 4
Hypotheses test						
Cons.	5.987 ***	5.719 ***	5.617 ***	Cons.	5.713 ***	5.609 ***
	(0.192)	(.193)	(0.200)		(.196)	(0.210)
Gender	−0.297 ρ	−.329 *	−0.324 *	Gender	−.315 *	−0.327*
	(0.173)	(.158)	(0.150)		(.160)	(0.153)
City	−0.217 ns	−.216 ns	−0.197 ns	City	−.238 ns	−0.226 ρ
	(0.174)	(.140)	(0.127)		(.146)	(0.131)
Education	−0.093 ns	−.082 ns	−0.285 ns	Education	−.146 ns	−.327 ρ
	(0.157)	(.149)	(0.175)		(.149)	(.174)
Practical experience	−0.092 ns	−.140 ns	−0.129 ns	Practical experience	−.119 ns	−.130 ns
	(0.152)	(.147)	(0.142)		(.146)	(.145)
Time on website	0.053 ns	.055 ns	0.018 ns	Time on website	.046 ns	0.040 ns
	(0.163)	(.096)	(0.082)		(.110)	(0.096)
TC (H1)		.285 *	0.608 ***	TC (H1)	.325 **	0.659 ***
		(.127)	(0.149)		(.125)	(0.168)
OR (H2)		.405	1.287 ***	ER (H3)	.423 ***	1.378 ***
		(.072) ***	(0.247)		(.067)	(0.292)
TC*OR (H4)			−0.971 **	TC*ER (H5)		−1.048 ***
			(0.264)			(0.302)
Model information						
Log pseudolikelihood	−308788.17	−227302.89	−210016.79	Log pseudolikelihood	−230585.82	−216345.88
Wald chi2(3)	8.72	–	–	Wald chi2(3)	–	–
Wald chi2(5)	–	57.60	–	Wald chi2(5)	92.63	–
Wald chi2(6)	–	–	167.64	Wald chi2(6)	–	172.14
Prob > chi2	0.1206	0.0000	0.000	Prob > chi2	0.0000	0.000
Pseudo R2	0.056	0.305	0.358	Pseudo R2	0.295	0.339

Note: two-tail test; ns stands for non-significant, ρ P < 0.1, * P < 0.05, ** P < 0.01, *** p < 0.001.

more likely to voluntarily respond to normal users' questions in OHCs.

The effect of online reputation (i.e., positive feedbacks) is significant in models 1 and 2. H2 is supported. Positive online feedback is a powerful indicator of personal reputation. Higher volume of positive feedbacks means a mental health service provider is highly approved, and they thus like to voluntarily respond to user questions. Namely, mental health service providers who have good online reputations in OHCs are more likely to respond to user questions.

The effect of economic rewards is significant in models 3 and 4. H3 is supported. Namely, mental health service providers in OHCs are also motivated by material rewards. For mental health service providers, receiving economic rewards could compensate for their professional burnout and stress. They thus have motivation to conduct more voluntary behaviors.

The effects of two interaction terms are significant in models 2 and 4. H4 and H5 are supported. Namely, intrinsic motivations and extrinsic motivations interact with each other and negatively influence mental health service providers' voluntary behaviors in OHCs. Only those who have completed chargeable appointments can review mental health service providers, while economic rewards are based on the volume of

chargeable appointments. This negative interaction indicates that higher volumes of chargeable behaviors could undermine mental health service providers' voluntary behaviors in OHCs for mental health.

4. Discussion

Based on the objective data crawled from an OHC for mental health, this study has explored how intrinsic motivations and extrinsic motivations influence mental health service providers' voluntary behaviors. The empirical results show that 1) both intrinsic motivation (i.e., technical competence) and extrinsic motivations (i.e., online reputation and economic rewards) positively influence mental health service providers' voluntary behaviors; 2) the interaction effects between intrinsic motivations and extrinsic motivations negatively influence mental health service providers' voluntary behaviors. These findings make two significant theoretical contributions and two practical implications to the OHC operation.

4.1. Theoretical contributions

First, we contribute to the literature on health professionals' voluntary behaviors in OHCs by incorporating the effects of economic rewards. Many studies have examined the effects of extrinsic motivation on normal users' knowledge sharing behaviors in VCs [24,44,46,47] or health professionals' knowledge sharing behaviors in OHCs [31]; however, they seldomly incorporate the economic reward and investigate its effects. Health professionals are human beings and are self-interested [38]. They also face severe professional burnout, e.g., low rewards [39]. Receiving economic rewards boosts health professional's income and alleviates their economic pressure, which is helpful for them to conduct more voluntary behaviors. This paper studies economic rewards and verifies its effects. This finding reminds scholars to take economic rewards into consideration when they investigate health professionals' online voluntary behaviors. This is our first theoretical contribution.

Second, we contribute to motivation theory by verifying a situation where intrinsic motivations and extrinsic motivations could negatively interact. Examining the effects of intrinsic motivations and extrinsic motivations is not novel at all; however, the negative interaction effects between intrinsic motivations and extrinsic motivations are seldom verified [37,40]. In addition, the findings of those limited studies are inconsistent. For example, some scholars propose and verify that extrinsic motivations negatively moderate the effects of intrinsic motivations [40], while others propose and verify that intrinsic motivations negatively moderate the effects of extrinsic motivations [37]. We have verified that intrinsic motivations and extrinsic motivations negatively interact. This finding provides insights into how to reconcile the inconsistency in prior studies [37,40]. For example, scholars could propose an interaction effect other than a moderating effect. This finding extends the motivation theory by incorporating a new situation that intrinsic motivations and extrinsic motivations could negatively interact. Future studies should be careful when they examine the relationships of intrinsic motivations and extrinsic motivations. This is our second theoretical contribution.

4.2. Practical implications

We address two practical implications to the managers in OHCs where mental health professionals could conduct both voluntary behaviors and chargeable behaviors. First, managers should direct more traffic to those mental health professionals who have a lower volume of online chargeable appointments. As our empirical results show, economic rewards could drive mental health service providers to conduct more voluntary behaviors. Directing more traffic could bring them chargeable appointments and motivate them to provide more voluntary behaviors in OHCs.

Second, managers should encourage those health professionals who have higher volumes of online appointments to conduct more voluntary behaviors. Our empirical results indicate that the interaction effects between intrinsic motivations and extrinsic motivations negatively influence mental health service providers' voluntary behaviors. Namely, extrinsic motivations (e.g., higher volumes of positive feedback or economic rewards) together with other factors could undermine the voluntary behaviors. OHC managers should pay attention to this.

4.3. Limitations

We admit three limitations in this study. First, we only had a small sample from a single OHC. Online counseling is a new kind of online health service in China. There are limited recognized mental health service providers online. *YiXinLi*, as one of the biggest platforms, wants to set strict criteria of mental health service provider recognition to ensure service quality and lead the industry. We thus got a small sample from a single community. The small sample and single sample source issue might undermine the generalization of our findings. In addition, we cannot differentiate that a question is answered via invitation or without invitation. We are not sure whether the incentive factors behind the two situations are the same or not. We appeal that future research could address the above issues. The expected findings could further improve our understanding of health professionals' voluntary behaviors in OHCs.

Second, more efforts are needed to explore the measurement of technical competence. We used education level, practical experience, and number of professional titles to measure technical competence and its impacts. Different from prior studies [56], the effects of education level and practical experience are insignificant. It is possible that providers who *voluntarily* list more titles are also more likely to engage in voluntary behavior because they are more engaged with the website generally. However, due to our limited data sample, we cannot squeeze more useful information to explore the potential underlying reasons. We suggest and also will revisit the measurement of technical competence and address this issue in future studies.

Third, we only included limited factors that influence mental health service providers' voluntary behaviors. Other factors such as trust can also impact individuals' health information seeking or contributing behaviors in OHCs [69,3,70]. We did not include those factors, which is addressed as a limitation of this study. Scholars could address them in future studies.

5. Conclusion

This study has explored how intrinsic motivations and extrinsic motivations influence mental health service providers' voluntary behaviors in OHCs for mental health. The empirical results indicate that intrinsic motivations (i.e., technical competence) and extrinsic motivations (i.e., online reputation and economic rewards) not only positively influence but also interact with each other and exert negative effects on mental health service providers' voluntary behaviors. These findings indicate that health professionals are also human beings and need economic rewards to do voluntary behaviors; however, too many economic rewards could undermine their voluntary behaviors.

Authors' contributions

Junjie Zhou conceptualized the original idea for the paper that was further developed and refined by Meiyun Zuo. Junjie Zhou and Cheng Ye were involved in the initial design of the study that was further refined by Meiyun Zuo. Junjie Zhou developed the initial theory and hypotheses for the paper, and Meiyun Zuo further enhanced and refined the framing and theorizing in the paper. Junjie Zhou and Cheng Ye collected the data for the study and performed the coding process. Junjie Zhou completed the data analysis, and Junjie Zhou and Meiyun

Zhou further completed the discussions and limitations.

Declaration of Competing Interest

None.

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References

[1] S. Barnett, S.C. Jones, S. Bennett, D. Iverson, A. Bonney, Perceptions of family physician trainees and trainers regarding the usefulness of a virtual community of practice, J. Med. Internet Res. 15 (5) (2013) e92.
[2] H. Fan, R. Lederman, S.P. Smith, S. Chang, How trust is formed in online health communities: a process perspective, CAIS 34 (1) (2014) 531–560.
[3] S. Fan, N. Cooling, J. Radford, D. Fabian, J. Brown, Building on the evaluation of STARS: using online repositories to support the general practice learning community, Eval. J. Australas. 14 (2) (2014) 25–41.
[4] A. Murad, R. Lederman, R. Bosua, S. Chang, J.D. Wark, Enhancing General Practitioners Participation in a Virtual Community of Practice for Continuing Medical Education: an Exploratory Study, Paper presented at the HIC (2017).
[5] A. Murad, R. Lederman, R. Bosua, S. Chang, M. Pirotta, et al., Health practitioner perceptions of using a health virtual community of practice for their continuing professional development, PACIS 2017 Proceedings, (2017).
[6] J.M. Goh, G. Gao, R. Agarwal, The creation of social value: can an online health community reduce rural–urban health disparities? Mis Q. 40 (1) (2016) 247–263.
[7] K. Huang, I. Chengalur-Smith, W. Ran, Not just for support: companionship activities in healthcare virtual support communities, Commun. Assoc. Inf. Syst. 29 (2014) 561–594.
[8] H. Liang, Y. Xue, S.K. Chase, Online health information seeking by people with physical disabilities due to neurological conditions, Int. J. Med. Inform. 80 (11) (2011) 745–753.
[9] L. Yan, Y. Tan, Feeling blue? Go online: an empirical study of social support among patients, Inf. Syst. Res. 25 (4) (2014) 667–891.
[10] S. Guo, X. Guo, Y. Fang, D. Vogel, How doctors gain social and economic returns in online Health-care communities: a professional capital perspective, J. Manag. Inf. Syst. 34 (2) (2017) 487–519.
[11] J. Zhou, L. Amo, C. Ye, S. Kai, Using reputation to predict online psychological counselor appointment: evidence from a chinese website, Proceedings of the 2018 ACM SIGMIS Conference on Computers and People Research (2018).
[12] J. Zhou, F. Liu, H. Zhou, Understanding health food messages on Twitter for health literacy promotion, Perspect. Public Health 138 (3) (2018) 173–179.
[13] P.Y. Collins, V. Patel, S.S. Joestl, D. March, T.R. Insel, A.S. Daar, et al., Grand challenges in global mental health, Nature 475 (7354) (2011) 27–30.
[14] D.L. Vogel, N.G. Wade, A.H. Hackler, Perceived public stigma and the willingness to seek counseling: the mediating roles of self-stigma and attitudes toward counseling, J. Couns. Psychol. 54 (1) (2007) 40–50.
[15] D.L. Vogel, S.R. Wester, L.M. Larson, Avoidance of counseling: psychological factors that inhibit seeking help, J. Couns. Dev. 85 (4) (2007) 410–422.
[16] N. Rüsch, M.C. Angermeyer, P.W. Corrigan, Mental illness stigma: Concepts, consequences, and initiatives to reduce stigma, Eur. Psychiatry 20 (8) (2005) 529–539.
[17] D.L. Vogel, S.R. Wester, To seek help or not to seek help: the risks of self-disclosure, J. Couns. Psychol. 50 (3) (2003) 351–361.
[18] J.R. Alleman, Online counseling: the internet and mental health treatment, Psychother. Theory Res. Pract. Train. 39 (2) (2002) 199–209.
[19] M.A. Feijt, Y.A. de Kort, I.M. Bongers, W.A. IJsselsteijn, Perceived drivers and barriers to the adoption of eMental health by psychologists: The construction of the levels of adoption of eMental health model, J. Med. Internet Res. 20 (4) (2018) e153.
[20] S. Haberstroh, G. Parr, L. Bradley, B.M. Fleming, R. Gee, Facilitating online counseling: perspectives from counselors in training, J. Couns. Dev. 86 (4) (2008) 460–470.
[21] J. Jin, X. Yan, Y. Li, Y. Li, How users adopt healthcare information: An empirical study of an online Q&a community, Int. J. Med. Inform. 86 (2016) 91–103.
[22] M. van der Eijk, M.J. Faber, J.W. Aarts, J.A. Kremer, M. Munneke, et al., Using online health communities to deliver Patient-Centered care to people with chronic conditions, J. Med. Internet Res. 15 (6) (2013) e115.
[23] L.L. Yan, Y. Tan, The consensus effect in online health-care communities, J. Manag. Inf. Syst. 34 (1) (2017) 11–39.
[24] Z. Yan, T. Wang, Y. Chen, H. Zhang, Knowledge sharing in online health communities: a social exchange theory perspective, Inf. Manag. 53 (5) (2016) 643–653.
[25] T. Yao, Q. Zheng, X. Fan, The impact of online social support on patients' quality of life and the moderating role of social exclusion, J. Serv. Res. 18 (3) (2015) 369–383.
[26] J. Zhou, Factors influencing people's personal information disclosure behaviors in online health communities: a pilot study, Asia Pacific J. Public Health 30 (3) (2018) 286–295.
[27] K. Rolls, M. Hansen, D. Jackson, D. Elliott, How health care professionals use social media to create virtual communities: an integrative review, J. Med. Internet Res. 18 (6) (2016) e166.
[28] S.A. Stewart, S.S.R. Abidi, Applying social network analysis to understand the knowledge sharing behaviour of practitioners in a clinical online discussion forum, J. Med. Internet Res. 14 (6) (2012) e170.
[29] M.J. Metzger, Making sense of credibility on the Web: models for evaluating online information and recommendations for future research, J. Am. Soc. Inf. Sci. Technol. 58 (13) (2007) 2078–2091.
[30] S. Atanasova, T. Kamin, G. Petrič, Exploring the benefits and challenges of health professionals' participation in online health communities: emergence of (dis)empowerment processes and outcomes, Int. J. Med. Inform. 98 (2017) 13–21.
[31] X. Zhang, S. Liu, Z. Deng, X. Chen, Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users, Comput. Human Behav. 75 (2017) 797–810.
[32] J. Gummerus, V. Liljander, M. Pura, A. van Riel, Customer loyalty to content-based web sites: the case of an online health-care service, J. Serv. Mark. 18 (3) (2004) 175–186.
[33] A. Bullock, Does technology help doctors to access, use and share knowledge? Med. Educ. 48 (1) (2014) 28–33.
[34] B.A. Hüttel, J.H. Schumann, M. Mende, M.L. Scott, C.J. Wagner, How consumers assess free E-Services: the role of Benefit-Inflation and Cost-Deflation effects, J. Serv. Res. 21 (3) (2018) 267–283.
[35] S. Guo, X. Guo, X. Zhang, D. Vogel, Doctor–patient relationship strength's impact in an online healthcare community, Inf. Technol. Dev. 24 (2) (2018) 279–300.
[36] X. Liu, X. Guo, H. Wu, T. Wu, The impact of individual and organizational reputation on physicians' appointments online, Int. J. Electron. Commer. 20 (4) (2016) 551–577.
[37] Y. Li, X. Ma, J. Song, Y. Yang, X. Ju, Exploring the effects of online rating and the activeness of physicians on the number of patients in an online health community, Telemed. E-Health (2019) Ahead of Print.
[38] A. Maynard, Is doctors' self interest undermining the National Health Service, BMJ 334 (7587) (2007) 234.
[39] H. Wu, L. Liu, Y. Wang, F. Gao, X. Zhao, et al., Factors associated with burnout among Chinese hospital doctors: a cross-sectional study, BMC Public Health 13 (1) (2013) 786.
[40] L. Zhao, B. Detlor, C.E. Connelly, Sharing knowledge in social Q&a sites: The unintended consequences of extrinsic motivation, J. Manag. Inf. Syst. 33 (1) (2016) 70–100.
[41] R.M. Ryan, E.L. Deci, Intrinsic and extrinsic motivations: classic definitions and new directions, Contemp. Educ. Psychol. 25 (1) (2000) 54–67.
[42] M. Hsu, T.L. Ju, C. Yen, C. Chang, Knowledge sharing behavior in virtual communities: the relationship between trust, self-efficacy, And Outcome Expectations International Journal of Human-Computer Studies 65 (2) (2007) 153–169.
[43] D. Liou, W. Chih, C. Yuan, C. Lin, The study of the antecedents of knowledge sharing behavior: the empirical study of Yambol online test community, Internet Res. 26 (4) (2016) 845–868.
[44] M.M.L. Wasko, S. Faraj, Why should I share? Examining social capital and knowledge contribution in electronic networks of practice, Mis Q. 29 (1) (2005) 35–57.
[45] Y.C. Zhao, Q. Zhu, Effects of extrinsic and intrinsic motivation on participation in crowdsourcing contest, Online Inf. Rev. 38 (7) (2014) 896–917.
[46] K. Marett, K.D. Joshi, The decision to share information and rumors: examining the role of motivation in an online discussion forum, Commun. Assoc. Inf. Syst. 24 (2009) 47–68.
[47] J. Lou, Y. Fang, K.H. Lim, J.Z. Peng, Contributing high quantity and quality knowledge to online Q&a communities, J. Assoc. Inf. Sci. Technol. 64 (2) (2013) 356–371.
[48] G. Bloom, H. Standing, R. Lloyd, Markets, information asymmetry and health care: towards new social contracts, Soc. Sci. Med. 66 (10) (2008) 2076–2087.
[49] M.R. DiMatteo, R. Hays, The significance of patients' perceptions of physician conduct, J. Community Health 1 (6) (1980) 18–34.
[50] T. Lagu, P.K. Lindenauer, Putting the public back in public reporting of health care quality, JAMA 304 (15) (2010) 1711–1712.
[51] G.G. Gao, J.S. McCullough, R. Agarwal, A.K. Jha, A changing landscape of physician quality reporting: analysis of patients' online ratings of their physicians over a 5-year period, J. Med. Internet Res. 14 (1) (2012) e38.
[52] A. Murad, R. Bosua, S. Chang, R. Lederman, P. Bednar, U. Frank, et al., Informing the Design of a Health Virtual Community of Practice: a Knowledge Translation Approach, Paper presented at the (2018).
[53] R. DeCharms, Personal Causation: the Internal Affective Determinants of Behavior, Academic Press, New York, 1968.
[54] S. Chai, S. Das, H.R. Rao, Factors affecting bloggers' knowledge sharing: an investigation across gender, J. Manag. Inf. Syst. 28 (3) (2011) 309–342.
[55] C.P. Lin, Gender differs: modelling knowledge sharing from a perspective of social network ties, Asian J. Soc. Psychol. 9 (3) (2006) 236–241.
[56] C.E. Edwards, N.L. Murdock, Characteristics of therapist self-disclosure in the counseling process, J. Couns. Dev. 72 (4) (1994) 384–389.
[57] S.Y. Hung, H.M. Lai, Y.C. Chou, Knowledge-sharing intention in professional virtual communities: A comparison between posters and lurkers, J. Assoc. Inf. Sci. Technol. 66 (12) (2015) 2494–2510.
[58] X. Cao, D. Wang, The role of online communities in reducing urban–rural health disparities in china, J. Assoc. Inf. Sci. Technol. 69 (7) (2018) 890–899.

[59] Y. Xiang, X. Yu, N. Sartorius, G.S. Ungvari, H.F. Chiu, Mental health in China: challenges and progress, Lancet 380 (9855) (2012) 1715–1716.
[60] M.E. Falagas, A. Zarkali, D.E. Karageorgopoulos, V. Bardakas, M.N. Mavros, The impact of article length on the number of future citations: a bibliometric analysis of general medicine journals, PLoS One 8 (2) (2013) e49476.
[61] T.A. Judge, D.M. Cable, A.E. Colbert, S.L. Rynes, What causes a management article to be cited—article, author, or journal? Acad. Manag. J. 50 (3) (2007) 491–506.
[62] M. Lyons, N.D. Aksayli, G. Brewer, Mental distress and language use: linguistic analysis of discussion forum posts, Comput. Human Behav. 87 (2018) 207–211.
[63] ChinaDaily, China's Health Literacy Rate Edges Higher in 2017, Retrieved from (2018) http://www.chinadaily.com.cn/a/201810/06/WS5bb8270fa310eff303280d3a.html.
[64] H. Yang, X. Guo, T. Wu, X. Ju, Exploring the effects of patient-generated and system-generated information on patients' online search, evaluation and decision, Electron. Commer. Res. Appl. 14 (3) (2015) 192–203.
[65] ChinaDaily, Top 15' new first-tier' cities in China, Retrieved from (2017) www.chinadaily.com.cn/business/2017top10/2017-05/15/content_29343927.htm.
[66] Wikipedia, List of Cities in China, Retrieved from (2018) https://en.wikipedia.org/wiki/List_of_cities_in_China.
[67] A.C. Cameron, P.K. Trivedi, Regression Analysis of Count Data, Cambridge University Press, Cambridge, United Kingdom, 2013.
[68] J. Du, Y. Park, N. Theera-Ampornpunt, J.S. McCullough, S.M. Speedie, The use of count data models in biomedical informatics evaluation research, J. Am. Med. Inform. Assoc. 19 (1) (2011) 39–44.
[69] M. Álvarez-Jiménez, J.F. Gleeson, S. Bendall, R. Lederman, G. Wadley, E. Killackey, et al., Internet-based interventions for psychosis: a sneak-peek into the future, Psychiatric Clinics 35 (3) (2012) 735–747.
[70] P.C. Pang, S. Chang, J.M. Pearce, K. Verspoor, Online Health Information Seeking Behaviour: Understanding Different Search Approaches, Paper presented at the PACIS (2014).