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Research on User Information Adoption in Online Health Communities

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Abstract: ***In order to speed up the operation and development of online health communities, enhance user stickiness, increase user satisfaction and activity, and better serve online health community users, this article is based on the traditional information adoption model architecture, through the three dimensions of information quality and the herd theory To measure the perceived trust, and based on the theory of perceived risk and health self-efficacy, the influencing factors of user information adoption in online health communities are studied, and the mechanism of action is explored. The research results show that: information quality and information heat significantly positively affect perceived trust, and perceived risk significantly negatively affects perceived trust, but it has no significant impact on user information adoption, and perceived trust and health self-efficacy significantly positively affect user information Acceptance, perceived trust plays a partly intermediary role in the relationship between information quality and user information adoption, and a complete intermediary role in the relationship between information popularity and user information adoption. The results of this study can provide relevant suggestions for online health community platforms to provide better information services to users, improve user satisfaction and increase activity.***

Keywords: Online health community, Health information, Perceived trust, User information adoption

1. Introduction

With the rapid growth of the population and the improvement of residents' health awareness, people's demand for medical services is increasing, and limited medical resources are not enough to meet people's needs in an all-round way. The rapid development of the Internet has contributed to this supply-demand relationship. Precise matching provides a perfect opportunity. "Internet + medical treatment" represents the new development direction of the medical industry, which is conducive to solving the contradiction between the imbalance of medical resources in China and the increasing demand for health and medical treatment. It is a medical development model actively guided and supported by the Ministry of Health.As of May 8, 2019, China has 158 Internet hospitals. The policy system of "Internet + medical health" has been basically established, with a market size of 27.17 billion yuan, and the industry is developing well. In 2020, more than half of Internet + medical product users in China will be more satisfied with the product and service, and will generally be more willing to purchase Internet + medical products in the future. [1].Among them, online health and medical services are an important part of the "Internet + medical" model. In this context, online health communities such as 39Health.com, Good Doctor Online, Dingxiangyuan, Baidu Health Tieba, and Tianmijiayuan have developed rapidly. The online health community can be divided into online doctor-doctor community, online doctor-patient interaction community and online patient-patient interaction community according to different service targets and communication modes [2] (as shown in Table 1).

The online health community provides a good platform for users to obtain health information services. Users can collect urgently needed health information by participating in community interaction and health information search, and analyze, evaluate and select related health information, and then Adopt it on the basis of perception and trust in health information.

Information adoption refers to the process of the subject's purposeful selection, evaluation, acceptance and use of information, and this process will ultimately affect the subject's subsequent behavior. In the online health community, user information adoption refers to the behavior of users to improve their health status based on the health information after receiving health information in the online health community [3]. Some scholars have conducted research on the influencing factors of information adoption behavior, and there are also some studies on health information adoption behavior in the field of online health care. Sussman and Siegal refer to the technology adoption model, based on the quality of the arguments and the credibility of the information source and the usefulness of the information, they proposed an information adoption model [4], which was later widely used in the research of network information adoption [5,6]. The technology acceptance model established by Davis proposes perceived usefulness, perceived ease of use and its advantages [7]. Factors such as perceived privacy risk may also have an impact on information adoption behavior [8].In the research of Chinese scholars, Yuet al. proposed a research model of mobile health service user adoption behavior based on the theory of perceived value and trust [9]. Based on the information adoption model, Tang et al. integrated into the social support theory, introduced the key role of health literacy and trust, constructed a causal model of information adoption willingness in the context of online health communities, and conducted research and analysis on related factors [10]. Mo and Deng conducted research on the regulation and mediation of health self-performance based on the analysis of the impact of the adoption of health information on social networking sites [11]. Wang et al. used college students as the research object and constructed a model of influencing factors of college students' online health information adoption behavior [3].

At present, there are relatively few studies on user information adoption in the field of medical and health services, and there are even fewer studies on user information adoption in online health communities with patient-patient interaction. The user groups in the online health community are diverse, and the adoption of health information by users (patients/patients' family members, etc.) also involves multiple factors. The adoption of health information is also different from the general information adoption, because it is related to the patient's health and even life safety.

Therefore, when users adopt health information, they need to analyze, evaluate and adopt relevant health information in multiple dimensions. Therefore, from the perspective of users' health information needs, this study considers the impact of perceived risk on perceived trust and user information adoption, plus the impact of users' health self-efficacy through the perception of trust in the quality and popularity of health information. , To in-depth study of the relevant factors influencing the adoption of user information in the online health community, in order to improve the service quality of the online health community, and increase the user's satisfaction and activity in the online health community.

Table 1: Overview of the classification of online health communities

Community type	Client	Service Function	Examples of related communities
Online doctor-doctor community	Professional groups such as scientific research workers, doctors, and scientists related to the medical field	Provide knowledge and information in medical, health, nursing, medicine, life science and other fields required for medical and health services	Lilac Garden
Online doctor-patient interactive community	Doctors and patient groups	Provide services for doctor-patient communication, health consultation and diagnosis	Good Doctor Online
Online patient-patient interactive community	Groups suffering from the same disease or different diseases	Provide services for patients/users to exchange and share health experiences	Post it for various chronic diseases, Sweet Home, Patients Like Me

2. Theoretical Model and Research Hypothesis

2.1 Information quality theory

Health information products and services in online health communities are very important to users, and they are also one of the important considerations for users to ultimately adopt health information. For this type of health information attributes, many scholars have conducted relevant research. Rieh S Y and others measure the quality of network information from 7 dimensions of source, content, format, presentation, timeliness, accuracy and loading speed [12]. Chinese scholars have established an information content quality evaluation system from the attributes of authority, accuracy, novelty, objectivity, completeness, and pertinence [13].In view of the particularity of online health information and the virtual nature of online health communities, users will have higher requirements for the source reliability, accuracy, and timeliness of the health information they need. Because, judging these dimensions of health information will enhance users' trust in related health information, so that they can be more adopted. The quality of health information in online health communities is very important to users. The higher the quality of health information, the more trustworthy it is, which helps users to adopt health information provided by online health communities. Therefore, this research proposes the following hypotheses:

H1. The quality of information in online health communities has a positive impact on users' perceived trust.
H1a. Source reliability has a positive impact on users' perceived trust.
H1b. Information accuracy has a positive impact on users' perceived trust.
H1c. Timeliness has a positive impact on users' perceived trust.

2.2 Herd theory

Conformity is a common phenomenon in social psychology, which refers to the process by which individuals change their actions and beliefs in order to adapt to the requirements of groups or groups. The earliest research on the phenomenon of herd is the "swimming illusion" experiment done by social psychologist M. Sharif in 1935-the study of how individual reactions are affected by the reactions of many other people [14]. Since then, the study of herd phenomenon has gradually emerged. Among them, the herding phenomenon in online shopping is the key research direction of scholars.

In the online health community, there are relatively few studies on the phenomenon of herd mentality. In the doctor-patient interactive community, studies have found that the popularity of patient recommendations has no significant effect on the amount of consultations from doctors. Although herd theory is related to patient selection, under the combined effect of other information, patients are directly related to doctors' services. The information is more sensitive [15]. In the patient-to-patient interactive community, users are not directly related to doctors, but are analyzed and evaluated through information provided by other users of the community platform (patients/patients' family members, etc.) before deciding whether to adopt relevant health information. Therefore, the popularity of health information provided in the community has a very important reference significance for whether users adopt the health information. Therefore, based on the theory of herd mentality affecting online consumption, it is proposed that the herding mental factors of users in online health communities are the influencing factors for users to gain perceived trust by adopting information. Users will obtain the perceived trust of information adoption from the information heat of health information in the online health community, that is, the comprehensive heat of related health information views, comments, and likes. Therefore, this research proposes the following hypotheses:

H2. The popularity of information in online health communities has a positive impact on users' perceived trust.

2.3 Perceived risk theory

Perceived risk is essentially a subjective risk, which was first proposed by Bauer from the perspective of psychology and introduced it into the field of consumption for research. Subsequently, scholars began to conduct research on perceived risk. In these studies, the relationship between perceived risk and perceived trust has always been a key research area. Among them, some studies have found that in the online shopping scenario, the higher the consumer's perceived risk of product purchase, the lower the degree of trust, and the consumer's willingness to buy will also decrease [16]. In the field of health information services in online health communities, because health information is more sensitive than other information and involves the physical health of patients, coupled with the virtual nature of the Internet, users search for health information in online health communities and perform Be more cautious when analyzing and evaluating. Therefore, users' concerns about the risks of providing health information on online health community platforms have led to the impact of users on their trustworthiness. Bansal and other studies found that the perceived risk of patients has a negative impact on trusting the websites they visit [17]. In the study of online health information, Mun et al. also found that the perceived risk of patients has a significant negative impact on trust [18]. Therefore, when the user's perceived risk is high, they will have a sense of distrust of the health information services in the online health community; otherwise, the user's sense of trust will be higher.

In addition, according to the BRA model, an important framework for decision analysis and consumer behavior research, consumers' willingness to consume is affected by their perceived risks. Chen et al. found that the perceived risk in online shopping scenarios has a significant impact on consumers' re-consumption intentions [19]. Similarly, in the field of online health services, Mou et al. empirically analyzed that the perceived risk in online health services has a significant impact on patients' behavioral intentions [20]. Research by Yao et al. also found that in the network environment, the perceived risk of users negatively affects user satisfaction [21]. As a result, in terms of health information services in online health communities, the higher the user's perceived risk of related health information, the lower their intention to adopt related health information may be.Therefore, this research proposes the following hypotheses:

H3. The perceived risk of users in online health communities has a negative impact on perceived trust.

H4. Perceived risks of users in online health communities have a negative impact on user information adoption.

2.4 Perceived trust theory

In terms of medical and health services, trust is very important in health services due to patients' needs for high accuracy, privacy and sensitivity of relevant health information [22]. Especially in the field of online health community medical treatment, coupled with the virtual nature of the network, patients lack access to relevant health information and experience of related treatments. Trust is even more important in the field of online health services.

In the field of technology adoption, trust is usually used as a key factor to study how to reduce the uncertainty of technology adoption [20]. Studies have found that users usually refuse to adopt information provided by users in unfamiliar online communities, because the results of their adoption may have a negative impact on users' finances, health, and privacy [23]. Therefore, lack of trust will seriously weaken users' willingness to adopt information.

In the field of online health care, studies have shown that users' trust in online health service community platforms has a positive impact on their use behavior [24].Guo et al. empirically analyzed the complete mediating effect of user trust on privacy concerns, perceived personality, and willingness to adopt information [23]. When studying the adoption behavior of information on Wikipedia by school groups and others, they found that trust has a completely mediating effect between information usefulness and information adoption behavior, and users' trust in health information positively affects users' willingness to adopt health information[25]. Harris research found that factors such as information quality and service perception of online health information have a significant impact on users' trust in online health information services [26].

At present, users collect health information through the Internet, and obtain treatment suggestions and emotional support more and more. In the online health community of patient-patient interaction, many users are eager to seek relevant health information to guide themselves because of their health needs. Improve their health conditions, but they lack relevant medical knowledge and treatment experience, which leads to questioning the accuracy, timeliness and authenticity of health information transmitted in online health communities [27], and the issue of trust is more prominent. The user's adoption of health information is closely related to their own health and must be cautious. Only enough trust can drive users to adopt health information. In the online health community, the comprehensive enthusiasm of the information quality of health information and the evaluation of the health information of the provided services helps to increase users' trust in the information services provided by the community platform. Therefore, this research proposes the following hypotheses:

H5. The perceived trust of users in online health communities has a positive impact on the adoption of user information.

H7. Perceived trust plays a mediating role in the relationship between information quality and user information adoption in online health communities.

H8. Perceived trust plays a mediating role in the relationship between information popularity and user information adoption in online health communities.

2.5 Healthy self-efficacy theory

Health self-efficacy refers to people's beliefs about whether they have the ability to control environmental events that affect their health. It is widely used in the field of medical and health to predict and analyze people's health behaviors. It is derived from self-efficacy-an important part of social cognition theory. It mainly refers to people's confidence in whether they have the ability to perform a certain behavior. The higher the individual's expectation of efficacy, the more inclined to make greater efforts [28]. Studies have shown that self- efficacy can significantly affect people's disease management behaviors, such as changing exercise, medication, and diet habits to affect the treatment effect of female heart disease patients [39]. At the same time, healthy self-efficacy will positively affect a healthy lifestyle [30]. In the field of online health services, self-efficacy also has an impact on the behavior of users searching for health information [31]. In China, some scholars have found that self-efficacy has a positive impact on users' information utilization ability. Self-efficacy interacts with the integrity and credibility of information. The better the user's personal self-efficacy, the better the acquisition and utilization of health information [32]. In the online health community, users with high self-efficacy will feel that they have the ability to change their physical health through efforts, and they are more likely to adopt health information that is beneficial to health provided by the community platform. Therefore, this research proposes the following hypotheses:

H6. The health self-efficacy of users in online health communities has a positive impact on user information adoption.

2.6 Research model

Based on the above theoretical foundation and research hypothesis, this research proposes a research model of the factors affecting user information adoption in the online health community with patient-to-patient interaction as shown in Figure 1. In this model, perceived trust is used as an intermediary variable to explore the effects of users' perceived trust in online health communities on the relationship between information quality, information popularity, and user information adoption. Among them, the definition of each variable is shown in Table 2.

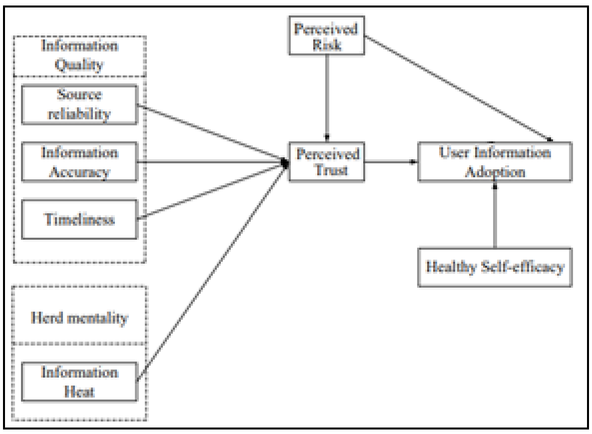

Figure 1: Research model of factors affecting user information adoption in online health communities

Table 2: Definition of research variables

Research Variables	Definition	Reference Source
Source Reliability	The user's trust attitude towards the information source and release channel on the platform.	Rieh S Y et al.[12]
Information Accuracy	Reduce the user's ability to select and jump among errors or useless information.	
Timeliness	The ability to update and present the latest information on the community platform.	
Information Heat	Comprehensive popularity of the number of views, comments and likes of health information on the community platform.	Q. Lu et al.[15]
Perceived Trust	Users trust the health information provided by online health communities.	Pappas [33]
Perceived Risk	Users encountering improper health knowledge services when accessing health knowledge services on the online health community platform will bear the risks of economic loss, waste of time and physical health.	MUN et al.[34] Hassan [35]
Healthy Self-efficacy	Users' perceptions of improving their health through the information services of the online health community.	Hyun et al.[36]
User Information Adoption	Users select and adopt various health information provided by online health communities.	Fan[37]

3. Method

This study uses a questionnaire survey method to collect sample data. There are 8 variables in the research model (as shown in Figure 1) on the factors affecting user information adoption in the online health community of patient-patient interaction, namely source reliability (SR), Information accuracy (IA), timeliness (TL), information popularity (IH), perceived trust (PT), perceived risk (PR), health self-efficacy (HSE) and user information adoption (UIA), with perceived trust as an intermediary variable. In order to ensure the validity and reliability of the questionnaire, the scale adopts the more mature measurement standards in relevant domestic and foreign literature, and adjusts accordingly according to the characteristics of the online health community, and finally formed a 27-element composition as shown in Table 3. In the online health community's user information adoption influencing factors research model scale, each measurement item is with a Likert 5-level scale. In order to ensure that the questionnaire has sufficient credibility, at least 3 measurement items are set for each variable.

4. Data Analysis

4.1 Data collection

This study uses a combination of field survey paper questionnaires and electronic questionnaires to collect data. The questionnaires for the field survey were mainly distributed in the Second Affiliated Hospital of Xi'an Jiaotong University, Xijing Hospital, and Shaanxi Provincial People's Hospital and its vicinity. The electronic questionnaires were produced using the "Questionnaire Star" platform and published in the WeChat group and QQ group of related diseases. Group and Baidu Tieba's disease Tieba and other patient-to-patient interactive online health community platform distribution. A total of 450 formal questionnaires were issued, of which 250 were paper questionnaires, 200 were electronic questionnaires, 86 invalid questionnaires were eliminated, and a total of 364 valid questionnaires were collected, with an effective recovery rate of 80.89%. The effective sample size is greater than 10 times the measurement item, which meets the requirements of sample stability.

4.2 Sample descriptive analysis

Descriptive analysis is usually used to study the basic situation of scale data. The average value is usually used to describe the overall distribution of sample data. The specific analysis is shown in Table 3:

Table 3: Descriptive analysis of research variables

Variable	Sample size	Minimum	Max	Average value	Standard deviation	Skewness	Kurtosis
SR	364	1	5	3.972	0.943	-1.096	0.809
IA	364	1	5	3.782	0.992	-0.877	0.01
TL	364	1	5	4.058	0.901	-1.206	1.086
IH	364	1	5	3.704	1.012	-0.404	-0.827
PR	364	1	5	2.728	1.059	0.268	-0.779
PT	364	1	5	3.683	1.053	-0.537	-0.828
HSE	364	**1**	5	3.967	0.888	-1.387	1.128
UIA	364	1	5	3.659	1.054	-0.564	-0.65

It can be seen from the above table that there are 364 samples in total. From the perspective of average and standard deviation, the average of the sample data is greater than the standard deviation, indicating that the volatility between the data is small and the data is relatively stable. From the perspective of sample skewness and kurtosis, the absolute value of kurtosis is less than 10, and the absolute value of skewness is less than 3, indicating that although the sample data is not completely normal, it is basically acceptable as a normal distribution.

4.3 Reliability and validity analysis

Reliability analysis is used to study the reliability and accuracy of answers to quantitative data; first analyze the α coefficient, if this value is higher than 0.8, it means that the reliability is high; if the value is between 0.7 and 0.8, it means that the reliability is good; If the value is between 0.6 and 0.7, the reliability is acceptable; if the value is less than 0.6, the reliability is not good. Re-analyze the reliability of the formal questionnaire, and the specific results are shown in Table 4:

Table 4: Cronbach reliability analysis

Factor	N	Cronbach α coefficient
SR	3	0.854
IA	3	0.859
TL	3	0.865
IH	3	0.924
PR	3	0.956
HSE	4	0.835
PT	4	0.893
UIA	4	0.924

It can be seen from the above table that the reliability coefficient values are all greater than 0.7, indicating that the reliability of the research data is of good quality. The validity test of the measurement model mainly evaluates its content validity, convergence validity and discriminative validity [38]. Among them, the content validity refers to the comprehensiveness of the research field and research content that the model can cover, and the measurement items of each variable in this article are derived from existing research, and are derived by revising the existing measurement items. Designing in conjunction with user interviews ensures the accuracy and comprehensiveness of the items. Therefore, it can be considered that the measurement items have good content validity. In order to test the convergent validity and discriminative validity of the model, this paper uses AMOS24.0 to conduct a confirmatory factor analysis. The test results are shown in Table 5. The standard factor loads of all variables are greater than 0.7, indicating that the measurement items can well represent the latent variables. The average extraction amount AVE was greater than 0.6, higher than the standard of 0.5; the combined reliability CR was greater than 0.8, higher than the standard of 0.7, indicating that the scale has good convergence validity.

Table 5: Relevant indicators of confirmatory factor analysis

Factor	Item	Standard factor loading	Cronbach α	CR	AVE
SR	SR1	0.794	0.854	0.853	0.659
	SR2	0.78			
	SR3	0.837			
IA	IA1	0.861	0.859	0.864	0.681
	IA2	0.835			
	IA3	0.868			
TL	TL1	0.834	0.865	0.869	0.691
	TL2	0.784			
	TL3	0.831			
IH	IH1	0.969	0.924	0.933	0.824
	IH2	0.873			
	IH3	0.897			
PR	PR1	0.986	0.956	0.958	0.883
	PR2	0.938			
	PR3	0.944			
HSE	HSE1	0.717	0.835	0.837	0.565
	HSE2	0.716			
	HSE3	0.825			
	HSE4	0.728			
PT	PT1	0.719	0.893	0.894	0.678
	PT2	0.791			
	PT3	0.815			
	PT4	0.84			
UIA	UIA1	0.894	0.924	0.925	0.754
	UIA2	0.86			
	UIA3	0.894			
	UIA4	0.857			

The discriminative validity can be tested by comparing the correlation coefficient between the square root of AVE and the latent variables. This article has carried out confirmatory factor analysis on the independent variables, intermediate variables and dependent variables of the structural model. The analysis and calculation results are shown in Table 6 and Table 7. As shown, it can be seen that the square root (diagonal) of all latent variables AVE is greater than its correlation coefficient with other latent variables, indicating that the difference between the measurement items is large, and the discrimination validity of each latent variable is good.

Table 6: Discrimination validity: Pearson correlation and square root value of AVE

	SR	IA	TL	IH	PR	HSE
SR	**0.812**					
IA	0.125	**0.825**				
TL	0.523	0.159	**0.831**			
IH	0.149	0.074	0.245	**0.908**		
PR	0.057	-0.018	0.033	-0.007	**0.94**	
HSE	0.48	0.324	0.451	0.094	0.07	**0.752**

Note: The diagonally bolded numbers are the square root value of AVE

Table 7: Discrimination validity: Pearson correlation and square root value of AVE (mediator variable and dependent variable)

	PT	UIA
PT	**0.823**	
UIA	0.37	**0.868**

Note: The diagonally bolded numbers are the square root value of AVE

4.4 Hypothesis testing

This paper uses AMOS24.0 to test the path coefficient of the model and verify whether the hypothetical relationship between the latent variables is established and verify the influence of the second-order latent variable IQ on PT. The test results are shown in Table 8 and Table 9. It can be seen from the test results that SR, IA, TL, IH have a significant positive effect on PT; HSE, PT have a significant positive effect on UIA; and PR has a significant negative effect on PT Impact relationship; but PR will not have a significant impact relationship on UIA; IQ will have a significant positive impact relationship on PT. AMOS test result diagram of the research modelis shown in Figure 2.

Table 8: Summary table of model regression coefficients

Y	<---	X	coef.	std. Error	z	p	std. Estimate
PT	<---	SR	0.325	0.073	4.433	***	0.3
PT	<---	IA	0.336	0.048	6.963	***	0.373
PT	<---	TL	0.165	0.068	2.413	0.016	0.162
PT	<---	IH	0.085	0.029	2.964	0.003	0.104
PT	<---	PR	-0.064	0.036	-1.791	0.073	-0.077
UIA	<---	PR	-0.048	0.045	-1.071	0.284	-0.051
UIA	<---	HSE	0.154	0.069	2.234	0.025	0.139
UIA	<---	PT	0.371	0.07	5.296	***	0.331

Note: → indicates the path influence relationship * p<0.1 ** p<0.05 ***p<0.01

Table 9: Model regression coefficient table

Y	<---	X	coef.	std.Error	z	p	std.Estimate
PT	<---	IQ	0.795	0.114	6.997	***	0.599

Note: → indicates the path influence relationship * p<0.1 ** p<0.05 ***p<0.01

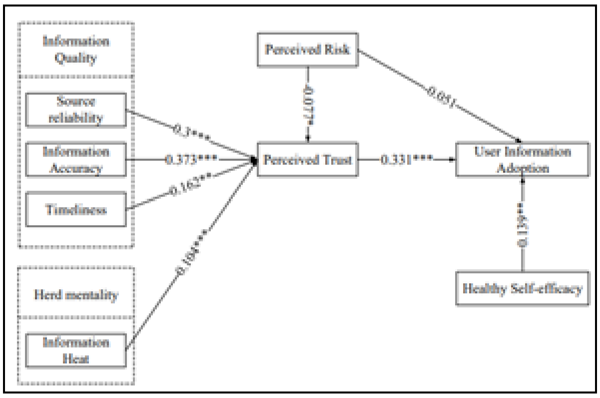

Figure 2: AMOS test result diagram of the research model.
* p<0.1 ** p<0.05 ***p<0.01

At the same time, this paper uses AMOS24.0 to test the fit of the structural equation model and the second-order information quality measurement model. The test results are shown in Table 10 and Table 11. The results show that the absolute fitness index, the value-added fitness index and the parsimonious fitness index mostly meet the standards, indicating that the overall model has a good fit validity and that the research model has good explanatory power.

Table 10: Fitting indexes of structural equation model

Index	χ^2/df	GFI	RMSEA	RMR	CFI	NFI	NNFI	TLI	AGFI	IFI	SRMR
Judgment criteria	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9	>0.9	>0.9	>0.9	<0.1
value	1.098	0.900	0.050	0.073	0.964	0.927	0.958	0.958	0.874	0.964	0.059

Table 11: Fitting indexes of the second-order measurement model of information quality

Index	χ^2/df	GFI	RMSEA	RMR	CFI	NFI	NNFI	TLI	AGFI	IFI	SRMR
Judgment criteria	<3	>0.9	<0.10	<0.05	>0.9	>0.9	>0.9	>0.9	>0.9	>0.9	<0.1
value	2.606	0.939	0.067	0.105	0.964	0.943	0.954	0.954	0.910	0.964	0.08

4.5 Mediating effect analysis

The following analysis of the mediation effect, the results are shown in Table 12:

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Table 12: Summary of Analysis of Mediation Effect

Path	point estimation	product of coef.		bias-corrected 90%CI		percentile 90%CI.	
		SE	z	Lower	Upper	Lower	Upper
Indirect effect							
IQ→PT→UIA	0.24	0.229	1.048	0.12	0.443	0.108	0.421
Direct effect							
IQ→UIA	0.294	0.278	1.058	0.025	589	33	0.6
Total effect							
IQ→UIA	0.534	0.143	3.734	0.32	0.776	0.334	0.794
Indirect effect							
IH→PT→UIA	0.022	0.016	1.375	0.003	0.054	0	0.049
Direct effect							
IH→UIA	0.048	0.039	1.231	-0.014	0.113	-0.012	0.116
Total effect							
IH→UIA	0.07	0.043	1.628	0.001	0.143	0.004	0.145

Note: Lower refers to the lower limit of the 90% interval of Bootstrap sampling, and Upper refers to the upper limit of the 90% interval of Bootstrap sampling.

Using Bootstrap sampling inspection method to conduct mediation research, the sampling frequency is 5000 times. From the above table, we can see: when IQ affects UIA, the mediation test of PT, the 90% interval of indirect effect, direct effect and total effect does not include numbers 0. It shows that PT has a partial mediating effect in the influence path of IQ on UIA. IQ will affect PT first, and then UIA through PT. Hypothesis H7: PT has a partial mediating effect in the relationship between IQ and UIA; for the impact of IH on UIA, PT acts as a mediating effect. The indirect effect and the 90% range of the total effect do not include 0, but 90% of the direct effect. The interval includes 0, which means that the direct effect is not significant, so it means that PT has a completely mediating effect in the path of IH's influence on UIA. Hypothesis H8: PT has an intermediary role in the relationship between IH and UIA, which is true.

5. Result

Synthesizing the analysis and discussion in the hypothesis test, this article draws the results of the research hypothesis. As shown in Table 13:

H1: IQ has a significant positive impact on PT; established
H1a: SR has a significant positive impact on PT; established
H1b: IA has a significant positive impact on PT; established
H1c: TL has a significant positive impact on PT; established
H2: IH has a significant positive impact on PT; established
H3: PR has a significant negative impact on PT; established
H4: PR has a significant negative impact on UIA; not valid
H5: PT has a significant positive impact on UIA; established
H6: HSE has a significant positive impact on UIA; established
H7: PT has a partial intermediary role in the relationship between IQ and UIA; established
H8: PT has a complete mediating role in the relationship between IH and UIA; established

Table 13: Summary table of hypothesis test results

Hypothesis	Variable relationship	test result
H1	Information quality has a positive impact on perceived trust	Established
H1a	Source reliability has a positive impact on perceived trust	Established
H1b	Information accuracy has a positive impact on perceived trust	Established
H1c	Timeliness has a positive impact on perceived trust	Established
H2	Information fever has a positive impact on perceived trust	Established
H3	Perceived risk has a negative impact on perceived trust	Established
H4	Perceived risk has a negative impact on user information adoption	invalid
H5	Perceived trust has a positive impact on user information adoption	Established
H6	Healthy self-efficacy has a positive impact on user information adoption	Established
H7	Perceived trust plays an intermediary role in the relationship between information quality and user information adoption	Partial intermediary
H8	Perceived trust plays an intermediary role in the relationship between information popularity and user information adoption	Fully intermediary

6. Discussion

This study explored the relevant factors influencing the adoption of user information in patient-patient interactive online health communities. Among them, information quality is composed of three dimensions: source reliability, information accuracy, and timeliness. The research results show that source reliability, information accuracy, and timeliness all have a positive and significant impact on perceived trust, and the standardized path coefficients are 0.325, 0.336, and 0.165, respectively. The results show that the source reliability, information accuracy and timeliness of health information in online health communities play an important role in enhancing users' perceived trust.

Starting from the user's social psychology, this study takes information popularity as an important factor influencing users' perception of trust in health information provided by community platforms. The analysis results show that information popularity has a positive effect on users' perceived trust, and its standardized path coefficient is 0.085. The research results show that the comprehensive popularity of health information will have important reference value for users to trust the information services provided by the community platform. Similar to the online shopping of goods by consumers, the comprehensive popularity of information such as sales volume, consumer reviews and page views of online shopping products will be affected. It has a significant positive impact on consumers' purchase intentions. This shows that there is a herd phenomenon in most consumer services. In the field of online health community medical service, the particularity and high sensitivity of health information, coupled with the virtual nature of the network, make users lack service experience. Therefore, users will be very cautious in adopting the health information provided by the community platform. They will refer to the health information provided by other users, especially those high-grade health information with their own health problems, and it will be easier for them to gain their trust and adopt relevant health information.

Risks have always existed in the field of medical and health services. In terms of medical information services in online health communities, the perceived risk of patients has always been a key research area. Data analysis shows that the impact of perceived risk on users' perceived trust is consistent with previous research results, and perceived risk will negatively and significantly affect users' perceived trust, with a standardized path coefficient of -0.064. This shows that the higher the user's perceived risk of the medical information service provided by the online health community platform, the lower the user's trust in its service, thus affecting the user's information adoption. In addition, the impact of perceived risk on user information adoption is not significant, with a standardized path coefficient of -0.048 and a P value of 0.284>0.01. This may be because in the field of online health community medical services, users' adoption of health information is not directly affected by perceived risk factors, but through other media. This is similar to previous research results in the field of online medical and health care that perceived risk does not significantly affect patients' behavioral intentions.

Health self-efficacy has an important influence on patients to improve their health. Research and analysis show that health self-efficacy has a positive and significant impact on user information adoption, which is consistent with previous research results, and its standardized path coefficient is 0.154.

In addition, trust has always been one of the key factors in the field of information adoption research. In the field of online health community medical services, users' perceived trust in community platform services is also one of the key factors in user information adoption. The results of this study show that in online health communities, perceived trust has a positive and significant impact on user information adoption, and its standardized path coefficient is 0.371. Regarding the mediating role of perceived trust, this study uses the Bootstrap sampling test method to find that perceived trust plays a part of the mediating role in the relationship between information quality and user information adoption, but also plays a role in the relationship between information popularity and user information acceptance. Complete mediation. This shows that the user's perceived trust plays a vital role in the entire process of user information adoption. In addition, although the comprehensive popularity of health information is an important reference factor for users to adopt information, it must act on user information adoption by influencing users' perceived trust. Therefore, gaining users' trust in online health community medical services is a key factor in promoting users' adoption of health information. The manager of the community platform optimizes the service quality of the community platform in many ways to enhance the user's perceived trust, thereby further promoting the user's information adoption, enhancing user satisfaction and platform user activity, and ensuring the operational growth and availability of the online healthy community. Continuous development.

7. Conclusion

This research focuses on the online health community research of patient-to-patient interaction, referring to the traditional information adoption model architecture, starting from the user's perspective, according to the user's special needs for health information, through the three dimensions of information quality and the herd mentality. The measurement of perceived trust proves that the increase in information quality and information popularity will effectively increase the user's perceived trust, which in turn will affect the user's information adoption; the increase in perceived risk will reduce the user's perceived trust, but does not significantly affect the user's information acceptance; and good Health self-efficacy will positively affect user information adoption and effectively improve the health of patients. This research enriches the theoretical system of user information adoption in online health communities, and can provide a certain reference for research in this field. In addition, the conclusions of this study have a certain reference value for the optimization of the platform management and operation mechanism of the patient-patient interactive online health community. The platform manager must strictly control the quality of the medical and health information on the community platform, especially for health. The reliability and accuracy of the source of the information should be reviewed, and relevant health information should be updated in a timely manner to avoid poor user service experience due to information time differences. In addition, users should also improve their health literacy and risk awareness. Before adopting relevant information, they should learn more about their health knowledge and platform service operation mechanisms related to their physical conditions to avoid medical service accidents. At the same time, users must have a good awareness of improving their health, strengthen their initiative, and effectively promote the improvement of their physical condition. As a result, by improving the service quality of the online health community, platform managers can increase the satisfaction and activity of users in the online health community, speed up the operation and development of the online health community, and users can more effectively receive medical treatment from the online health community. Health services to improve your health.

Appendix A. Measurement scales

Information quality (IQ：SR，IA，TL)

Source reliability (SR)

SR1.I think most of the information providers in the online health community are experienced and professional people.

SR2.I think most of the information in the online health community is more reliable.

SR3.I think the information in the online health community is often adopted by most people.

Information accuracy (IA)

IA1.Online health community provides a lot of irrelevant information, and I need to spend a lot of effort to filter the information I need.

IA2.I can quickly locate or find the information I need in the online health community.

IA3.I can usually get information and services that meet my personal needs in the online health community.

Timeliness (TL)

TL1.I believe that the online health community can frequently update the health information in it.

TL2.I often get the latest health Q&A information in the online health community.

TL3.Online health community can provide me with the latest health information.

Information Heat (IH)

IH1.I think the health information content that has a high number of views in the online health community is more reliable.

IH2.I am more interested in health information with a large number of comments in the online health community.

IH3.I agree with the health information that has a high number of likes in the online health community.

Perceived trust (PT)

PT1.I trust the health information and services provided by the online health community.

PT2.I think the online health community can meet the needs of users.

PT3.I think online health communities are more concerned about the interests of users.

PT4.I think other users participating in the online health community are trustworthy.

Perceived risk (PR)

PR1.I am worried that improper online health information services will cause economic losses.

PR2.I am worried that the lack of solutions to improve health in the online health community will cause a waste of time.

PR3.I am worried that false information will harm my health.

Healthy self-efficacy (HSE)

HSE1.I believe I can have a positive impact on my health.

HSE2.I have set certain goals to improve my health.

HSE3.I have achieved the goal I set to improve my health.

HSE4.I am actively working to improve my health.

User information adoption (UIA)

UIA1.The health information obtained from the community platform helps me understand the relevant conditions and act as soon as possible

UIA2.I agree that the community platform provides health information recommendations that are more in line with my own health status.

UIA3.Health case information with goodtreatment will motivate me to solve my health problems.

UIA4.Regarding my health status, I will pay close attention to various health information in the community platform and look forward to adopting.

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