Journal of Global Information Management
Volume 29 • Issue 5 • September-October 2021

Factors Influencing Chinese Online Health Service Use:
A Valence Framework Perspective

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ABSTRACT

Despite the popularity of online health services (OHSs) among patients in recent years, academic research on this phenomenon is limited. Drawing on the valence framework, the authors proposed a model to explore both the most important facilitators of OHS use intention from the perceived value perspective and inhibitors of OHS use intention from the perceived risk perspective. Data were collected from 407 OHS users through an online survey. Results showed that the inhibitors of OHS use intention include privacy risk and social risk, while facilitators include social support value, convenience value, and utilitarian value. These findings enrich the OHS literature by revealing both the inhibitors and facilitators of OHS use intention. This study also provides practical implications for platforms offering OHS in relation to effectively attracting users.

KEYWORDS

Online Health Service, Perceived Risk, Social Support, Utilitarian Value, Valence Framework

INTRODUCTION

In many countries, acquiring medical support is expensive and inconvenient. For some countries where medical treatment is free, it is necessary to make an appointment with a practitioner, and often the patient must wait a long time to receive medical treatment. In contrast, in countries where part of the medical cost must be paid by the patient, this cost is generally high and meeting them can be difficult for some patients (Qu, Li, Liu & Mao 2012). Recognizing this, many platforms offering online health services (OHS) have been launched in recent years, and have been widely accepted by patients (Zhang, Guo, Wu, Lai & Vogel 2017). An OHS is defined as "a form of Internet-based health service delivery in terms of professional health services and medical consultations"(Zhang, Guo, Wu, Lai & Vogel 2017, p.987). OHS platforms provide background information (affiliations, titles, expertise, among others) and online information on physicians (patients' reviews, interactions with patients, medical advice, among others), based on which patients can choose their physicians. Patients are also able to access health information, consultations, and recommendations by request

DOI: 10.4018/JGIM.20210901.oa8

at a price of 150–200 Yuan (about US $25–30) for every 15-minute phone call, or at a price of 20 Yuan (about US $3) for every question posed online.

Due to their many advantages, OHS have been warmly received by patients since they emerged in the e-marketplace. By April 2019, the number of active users of OHS reached 45 million in China. In 2018, the total revenue of the OHS market in China reached CNY49.1 billion (approximately US $7 billion), an increase of 45.87% from 2017, and this revenue is expected to reach CNY90 billion (approximately US $12.85 billion) in 2020 (Analysys 2018). A 2018 survey of Chinese citizens found that 73.85% of Chinese people say they are willing to pay for OHS (Analysys 2018).

Recognizing the benefits of OHS, many studies have been conducted focused on examining the benefits of adoption of OHS by examining the facilitators of user acceptance (e.g., Mou & Cohen 2014; Zhang, Liu, Deng & Chen 2017). However, it is important to have a more comprehensive understanding of OHS beyond this optimistic picture by also looking at possible barriers to acceptance as OHS are sometimes considered to pose various risks and threats. According to a report by Analysys (2018), 33.96% of people indicate that they are afraid to lose control of their private information, while 41.51% of people indicate that they are afraid to delay treatment of their health issues by using OHS.

In general, it is well-established in information systems (IS) research that beyond the technological and business aspects, user views on technology-based applications are a key determinant for the success of that technology (Venkatesh, Speier & Morris 2002). Furthermore, a service innovation will only be successful when it is accepted by the market (Cocosila & Trabelsi 2016). Research has shown that there are many factors that can potentially affect the perceptions and attitudes of target consumers regarding a new technology and ensure its acceptance and ultimate success (Cocosila & Trabelsi 2016; Xiao, Guo & D'Ambra 2017). While positive views, such as perceived usefulness, benefits, or ease of use are favorable factors, negative views like the perception of risk are deterrents for the use of a new technology. Accordingly, a comprehensive adoption investigation should integrate both favorable and unfavorable factors in a theoretically sound model (Cocosila & Trabelsi 2016). In addition, when studying all important and related variables separately, little is known as to whether any or all of these variables still play direct roles in influencing user online behavior when the effects of all variables are considered simultaneously (Xiao, Guo, D'Ambra & Fu 2016). Cocosila & Trabelsi (2016) also argue that a comprehensive investigation of technology adoption should integrate both facilitating and inhibiting factors in a theoretically sound research model. However, most previous literature has focused on explaining the enablers/facilitators of OHS use intention (Li, Wang, Lin & Hajli 2018; Yan, Wang, Chen & Zhang 2016), with limited attention devoted to the impacts of inhibitors. Zhang et al.(2017) conducted a study based on status quo bias perspective to explore the inhibitors of OHS use intention. However, their study does not consider both the facilitators and inhibitors and their study focus on inhibitors from traditional health services perspective. They called for more studies to explore other inhibitors not related to traditional health services. Therefore, this study aims to identify the facilitators of OHS use intention from the perceived value perspective and inhibitors of OHS use intention from the perceived risk perspective. Seeking insights into these factors will not only enable OHS providers to develop effective promotional strategies, but also enhance our understanding of the enablers and inhibitors from an integrative perspective. The following research question is investigated in this study:

RQ: What is the combined effect of perceived value and risk on the adoption of OHS?

The remainder of this paper is organized as follows. We first review the literature on OHS and the theoretical background of this study, including valence frameworks, perceived risks, and perceived values. The research framework and the research hypotheses are then presented, followed by the research methodology and the results of the data analysis. The key findings and implications are then discussed based on the results. This paper concludes with the research limitations and possible directions for future research.

LITERATURE REVIEW

OHS

OHS can be regarded as the application of e-commerce in the health context by providing an online platform for doctors to deliver health services requested by patients (Zhang, Guo, Wu, Lai & Vogel 2017). An increasing number of OHS platforms have been launched due to the increasing number of people searching online for health information. For instance, the most popular Chinese OHS platform, Hao Daifu Zaixian, has attracted more than 10,000,000 patient visits since its launch in 2006. Due to the limitations of Internet-based technologies and the special requirements of the treatment of diseases, only a limited range of health services (e.g., provision of professional healthcare information and medical consultations, and conducting patient education) can be provided on OHS platforms (Zhang, Guo, Wu, Lai & Vogel 2017). Patients with different diseases can search for information on OHS platforms to learn more about diseases, obtain a second opinion on their treatment, become more involved in health decision-making, seek emotional support after treatment, and access healthy lifestyle choices (Fisher, Burstein, Lynch & Lazarenko 2008; Zhang, Guo, Wu, Lai & Vogel 2017).

As OHS have become increasingly popular in recent years, researchers have begun to investigate this phenomenon. We summarize the studies examining users' behavior in the OHS context in Table 1 below. These studies generally fall into three categories. The first category focus on patients' online health information search intentions (Graffigna, Barello, Bonanomi & Riva 2017; Mou, Shin & Cohen 2017). For instance, based on the theory of planned behavior, Bao, Hoque & Wang (2017) explored the determinants of adult children's intention to use online health information for their elderly parents. They found that attitude, subjective norms, perceived behavior control, and risk were the predictors of intention to use online health information. The second category of studies focus on either patients' or physicians' information-sharing behavior in online health communities (Yan, Wang, Chen & Zhang 2016; Zhang, Guo, Xu & Li 2020). For instance, Zhang, Liu, Deng & Chen (2017) examine the motivation for sharing knowledge in online health communities for both health professionals and users. They found that reputation, reciprocity, knowledge self-efficacy, and altruism are motivations for health professionals to share knowledge in online health communities while reciprocity, altruism, and empathy are motivations for users. The third category of studies focus on patients' online consultation intention (Chang, Hsu, Wang & Chang 2019; Yang, Guo, Wu & Ju 2015). For instance, Chang, Hsu, Wang & Chang (2019) found that four justice dimensions, including distributive justice, procedural justice, interpersonal justice, and informational justice can influence trust and satisfaction, which further impact patients' continued intention to consult doctors online.

Although these studies have provided some insights into users' behavior in OHS, most have focused on examining users' health information-seeking behavior. As well as health information, online platforms and communities also provide online medical consultations. However, the use of such services is relatively low. Thus, more academic studies are needed to understand the facilitators and inhibitors that jointly influence user behavior. We intend to explain user OHS adoption based on a valence framework by considering both the inhibitors and facilitators of acceptance of these platforms.

Valence Framework

Proposed by Peter and Tarpey (1975), the valence framework use a "cognitive-rational" user decision-making model to explain individuals' decision-making behavior by considering both positive and negative attributes (Peters & Tarpey 1975). Derived primarily from the economics and psychology literature, this framework considers perceived benefit and perceived risk to be the two fundamental aspects of individual decision-making. The perceived benefit aspect assumes that individuals are motivated to maximize its positive aspects, while the perceived risk aspect characterizes individuals as motivated to minimize any expected negative effect (Li, Wang, Lin & Hajli 2018). Thus, the central premise of the valence framework is that individuals make decisions to maximize the net valence resulting from negative and positive effects (Kim, Ferrin & Rao 2008).

Table 1. Studies examining users' behavior in the OHS context

Authors	Methodology	Key influencing variable	Final outcome variable	Context
Atanasova, Kamin & Petric (2018)	Qualitative research (interview)	Emotional support; informational support; network	Online professional-patient interactions	The aim of this study is to explore and compare the benefits and challenges of online professional-patient interactions for users and health professional moderators and the effects of face-to-face medical encounters
Bao, Hoque & Wang (2017)	Empirical study	Attitudes; behavioral control; intention; risk; subjective norms; trust	Intention to use online health information	This study extends the Theory of Planned Behavior to identify the determinants of adult children's intention to use online health information for their aged parents
Chang, Hsu, Wang & Chang (2019)	Empirical study	Distributive justice; informational justice; interpersonal justice; procedural justice; satisfaction; trust	Continued intention to consult	This study aims to investigate how doctor-patient online interaction affects the integration of online and offline health services
Graffigna, Barello, Bonanomi & Riva (2017)	Empirical study	Medication adherence; quality of the patient-doctor relationship; patient empowerment; patient health management	Online health information seeking behavior	This study aims to identify the variables affecting patients' online health information-seeking behavior
Mano (2014)	Empirical study	Online health information; social media that offer consulting service	Use of OHS	This study investigates how differences in the use of online health information and social media affect the use of online health services
Mou, Shin & Cohen (2017)	Longitudinal study	Confirmation; perceived usefulness; satisfaction; subjective norms; trust in provider	Intention to use online health information service	This study draws on the theory of reasoned action and expectation–confirmation theory in a longitudinal study of trust in e-services to examine how trust interacts with other consumer beliefs such as perceived usefulness and how these beliefs together influence consumer intentions and behaviours concerning OHS at both the initial and latter stages of use.
Xiao, Sharman, Rao & Upadhyaya (2014)	Empirical study	Access to the Internet; communication quality with doctors; perceived health status; trust in online health information;	Online health information search	This paper examines the impacts of IT enablers and health motivators on peoples' online health information search behavior
Yan, Wang, Chen & Zhang (2016)	Empirical study	Cognitive cost; executional costs; face concern; reputation; sense of self-worth; social support	General knowledge sharing behavior; specific knowledge sharing behavior	This study examines the factors that influence specific and general knowledge sharing in online health community.
Yang, Guo, Wu & Ju (2015)	Empirical study	Patient generated information; system generated information	Patients' search for physicians' information on OHS website; Patients' decision to consult a physician online	This paper develops a two-equation model to verify the effects of two kinds of information on patients' search, evaluation and decision-making on healthcare websites
Zhang, Guo, Wu, Lai & Vogel (2017)	Empirical study	Health service habits; perceived benefits; perceived cost; privacy protection beliefs; sunk costs; transition costs	OHS use intention	This study draws on the status quo bias theory and the rational choice theory to explore the inhibitors of OHS use intention

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Table 1. Continued

Authors	Methodology	Key influencing variable	Final outcome variable	Context
Zhang, Sun & Kim (2017)	Empirical study	Demographics; health literacy; health status; personality; preference for information; source experience	Source selection for health search tasks	This study investigates how the individual characteristics of users influence their selection of five internet sources (search engines, social Q&A sites, online health communities (OHCs), social networking sites (SNSs), and crowdsourcing sites), for three distinct types of health search tasks (factual, exploratory, and personal experience).
Zhang, Guo, Xu & Li (2020)	Empirical study	No. of gifts; No. of patients; No. of readings; No. of votes	Free information sharing	Drawing on motivation theory, this study develops a theoretical model to explore the influences of material and professional motivation on free information sharing and the contingent roles of professional expertise and online expertise.
Zhang, Liu, Deng & Chen (2017)	Empirical study	Altruism; empathy; knowledge; reciprocity; reputation; self-efficacy	Knowledge sharing intention in online health communities	This study examines both the extrinsic and intrinsic motivations of health professionals and normal users.

The valence framework is powerful in explaining individuals' decision-making behavior in an online environment, as demonstrated in the literature (Gao & Waechter 2017; Lin, Wang, Wang & Lu 2014). For example, Lu et al. (2011) adopted the valance framework to explore the negative valences of perceived cost and perceived risk, and the positive valences of relative advantage, compatibility, and image, on consumers mobile payment services adoption intention. Gao and Waechter (2017) applied the valence framework to investigate consumers' initial trust facilitators and inhibitors in their adoption of mobile payment services. The positive valences they identified include perceived system quality, information quality, and service quality, while the negative valences they identified include perceived uncertainty. Li et al. (2018) developed a model based on the valence framework to explore users' health information seeking and sharing intention on social media. Xiao and Li (2019) developed a research model to investigate the perceived benefits and potential risks brought by positive online reviews. When people make decisions to use OHS, they are exposed to both negative valences in terms of perceived risks due to uncertainty and positive valences in terms of perceived value. Thus, it is appropriate to adopt this framework to explore both the inhibitors and facilitators of OHS use intention.

Perceived Risk

Perceived risk is defined as "subjectively determined expectation of loss" (Mitchell 1999, p.168). In other words, risk is the possibility that the product will not offer the expected benefits (Roselius 1971). Perceived risk has been widely used to explain consumer behavior (Xiao & Li 2019). It has become popular in IS research as well in recent years, especially in technology adoption studies (Cocosila & Trabelsi 2016; Featherman & Pavlou 2003). As new IT artifacts have become increasingly refined and complex, researchers have also detected the influence of some risk factors unfavorable to adoption by capturing various user fears (e.g., of wasting time or money, or of being exposed to physical or social discomfort), even if these fears may not correspond to actual dangers. Thus, perceived risk has been demonstrated to have a negative effect on the intention to adopt a new technology (Cocosila & Trabelsi 2016).

Perceived risk has been refined and developed by several scholars (Mitchell & Greatorex 1988), who argue that perceived risk has several facets, including financial risk (the purchase may be a waste of money), time risk (the purchase may be time-consuming), physical risk (the product or service may pose a physical risk), social risk (significant other people for the buyer may disapprove of the purchase), and privacy risk (the users' personal information may be used without permission).

When investigating users' views regarding OHS adoption, theoretical reasoning indicates that only physical risk, social risk, and privacy risks are worth consideration: patients may fear their personal health information will be shared without their permission, that they may receive incorrect diagnoses and misleading advice, or lose status in their social group by adopting a service that appears foolish. As the majority of OHS are free and only consultations with physicians cost a small sum of money, financial risk can be ignored. Time risk is not a concern, as OHS have the advantage of saving time compared to seeking medical service offline in hospitals.

Perceived Value

The concept of perceived value is popular in consumer behavior studies, and is acknowledged as a comprehensive multifaceted perception combining cognitive and emotive aspects of individuals' views regarding the consumption of goods or services in various choice situations (Rezaei & Ghodsi 2014). Perceived value is seen as a difference between the gains and the cost relative to a product or activity (Zeithaml 1988). Drawing on this foundation, in IS research the "gain" in the value associated with the use of technology can be expressed broadly as a combination of an extrinsic and cognitive benefit on one hand and of an intrinsic and affective benefit on the other hand (Kim, Chan & Gupta 2007). The extrinsic and cognitive benefits are related to the perception of the utilitarian value of a product or service, while the intrinsic and affective benefits are an expression of the hedonic value of that good or service (Al-Debei & Al-Lozi 2014). In addition to these, a third benefit that may be significant for user views of a technology is the social aspect of the value (Cocosila & Trabelsi 2016). Thus, consumer behavior and the IS literature show that, in addition to the utilitarian and hedonic sides, there is a social dimension of value, which captures the improvement of the user's self-image associated with the adoption of a product or technology, as purchasing these goods also has meaning in the buyer's community (Sweeney, Soutar & Johnson 1999).

When investigating users' reviews on OHS adoption, we argue that the utilitarian and social aspects of value should be considered since OHS provide convenience and cost saving to users and enable them to gain social support. Hedonic value is not a concern as OHS are not used for hedonic purposes.

RESEARCH MODEL AND HYPOTHESES

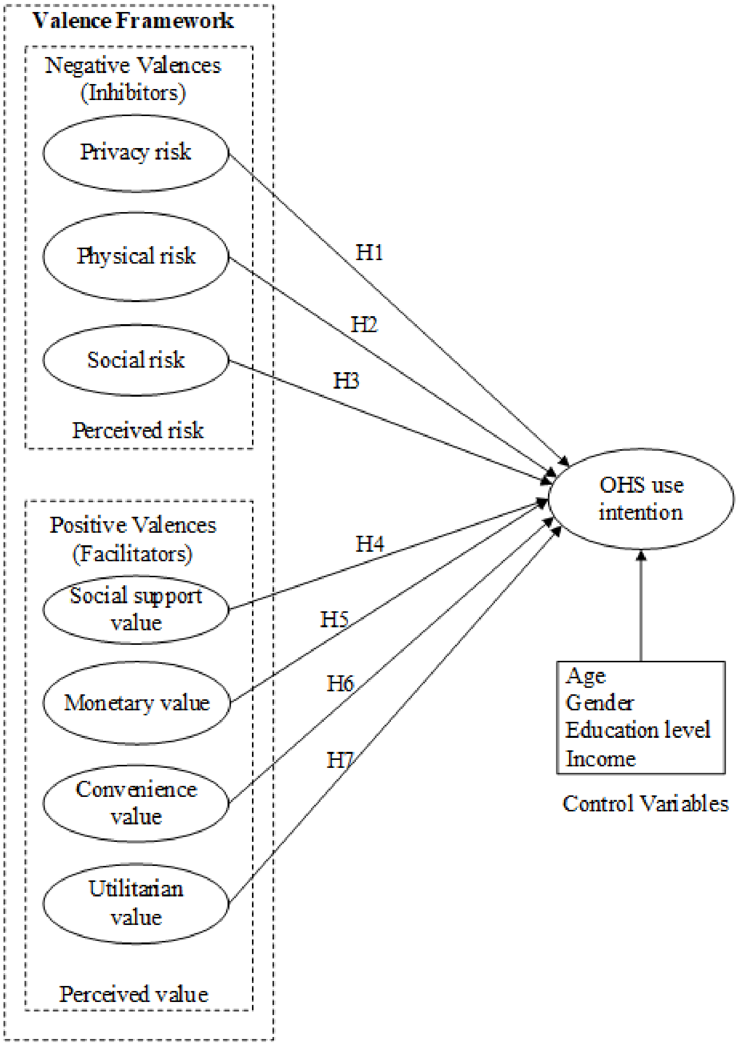
We developed a research model to examine the inhibitors and facilitators of OHS use intention from perceived risk and perceived value perspectives, respectively (see Figure 1), based on the theoretical background. It is hypothesized that the inhibitors (privacy risk, physical risk, and social risk) and the facilitators (social support value, monetary value, convenience value, and utilitarian value) can influence OHS use intention. In the following sections, we provide the justification for the hypotheses in our research model.

Negative Valence

Privacy Risk

Privacy risk refers to individuals' concern about potentially losing control of their personal information in situations where this information is used or shared without their knowledge or permission (Featherman & Pavlou 2003; Zhu & Bao 2018). Compared with traditional health services based in hospitals, individuals are more likely to suffer the loss of private information in the OHS context.

Figure 1. Research Model



For example, individuals must provide details about their health issues to physicians or other users on the platform to obtain relevant health information and advice (Bansal, Zahedi & Gefen 2010). This information is generated on websites rather than on paper documents or internal networks, as is the case in the context of traditional offline health services. The information provided online can be used or sold by the online health platform without the individual's permission. A 2018 report by Analysys (2018) found that 33.96% of people indicated that they were afraid to lose private information through using OHS. Therefore, it is hypothesized that:

H1: Privacy risk is negatively associated with OHS use intention.

Physical Risk

Physical risk refers to potential harm to the health of individuals (Herrera & Blanco 2011). In the OHS context, users may receive incorrect diagnoses and misleading advice for two principal reasons.

First, some physicians are not certified in the same manner as are physicians in traditional offline health services. These physicians may not be qualified to provide medical advice. Second, physicians on OHS must make decisions based only on the patient's description or on available medical test results, rather than doing a physical check or conducting medical testing by themselves. Thus, they may make incorrect diagnoses, which can harm the health of individuals (Atanasova, Kamin & Petric 2018). It is also difficult for users to protect their interests if an incorrect diagnosis harms their health due to the lack of appropriate law in the OHS context (Bernhardt, Lariscy, Parrott, Silk & Felter 2002). The report by Analysys (2018) found that 41.51% of people indicated that they were afraid to delay having their health issues treated by using OHS. Therefore, following hypothesis is proposed:

H2: Physical risk is negatively associated with OHS use intention.

Social Risk

Social risk refers to the potential for an individual to lose their status in their social group; this can result from events such as adopting a service or product that is considered inferior or from appearing foolish or unfashionable (Featherman & Pavlou 2003). People tend to maintain a good image of themselves in front of other people (Li, Wang, Lin & Hajli 2018). People may believe they will look foolish if others know they are accessing a health service from an online platform instead of from physicians in a hospital. Thus, individuals may experience social risk through OHS use. Li et al. (2018) found that social risk negatively influence individuals' health information-seeking intentions on social media. Thus, it is hypothesized that:

H3: Social risk is negatively associated with OHS use intention.

Positive Valence

Social Support Value

Social support is defined as "the perceived level of care, love, and support that an individual receives from members of a group" (Cobb 1976, p.300). This includes informational and emotional support. Previous research has demonstrated that one of the motivations for individuals to adopt OHS is to obtain social support (Maloneykrichmar & Preece 2005). In online health communities, people can access a large amount of health information, which is valuable for them to manage their health issues (Hajli, Bugshan & Lin 2013). In addition, users can receive emotional support from physicians or other patients in the online community with the same disease because in the online environment, which offers anonymity, patients may feel less pressure and more able to express their concerns and anxieties related to their health issues (Atanasova, Kamin & Petric 2018). Therefore, platforms offering OHS can provide both informational and emotional support to users. We expect that the more social support users obtain from using OHS, the more likely they are to adopt OHS. Therefore, the following hypothesis is proposed:

H4: Social support is positively related to OHS use intention.

Monetary Value

In the OHS context, monetary value refers to users' perception that pricing policies and levels of the OHS are acceptable and fair to users (Carlson, O'Cass & Ahrholdt 2015). Individuals tend to seek products and services that are affordable, fair, and reasonably priced (Carlson, O'Cass & Ahrholdt 2015). Thus, the monetary value of health services provided via the internet is important because users will compare prices for OHS with those in traditional offline health services. Zhang et al.

(2017) propose that OHS are offered at lower costs than services offered by traditional offline health services. Therefore, the following hypothesis is proposed:

H5: Monetary value is positively related to OHS use intention.

Convenience Value

In the OHS context, convenience value refers to saving time and effort by using an OHS (Jiang, Yang & Minjoon 2013). It is known that individuals will use an OHS if they perceive it is more convenient than using traditional offline health services (Zhang, Guo, Wu, Lai & Vogel 2017). In the context of traditional offline health services, users must make an appointment before accessing a health service and must receive treatment during the office hours. However, in OHS, users can seek health information anytime and anywhere. That is, OHS are able to provide greater location and time flexibility than traditional offline health services. Thus, OHS can increase accessibility and reduce waiting times. Therefore, the following hypothesis is proposed:

H6: Convenience value is positively related to OHS use intention.

Utilitarian Value

In the OHS context, utilitarian value is defined as individuals' perception that OHS can help them better manage their health issues (Li, Wang, Lin & Hajli 2018). Utilitarian value reflects several cognitive aspects of individuals' perceptions; for example, judgment of service efficiency, effectiveness, and results (Overby & Lee 2006). Previous studies have demonstrated that people consider utilitarian value when deciding whether to adopt certain technologies or technology-related services (Cocosila & Trabelsi 2016; O'Brien 2010). If the individual perceives the utilitarian value of using an OHS is high, this can lead to them overcoming barriers associated with OHS adoption (e.g., privacy risk) (Porter & Donthu 2006). Therefore, the following hypothesis is proposed:

H7: Utilitarian value is positively related to OHS use intention.

METHODOLOGY

Measures

The measures of all variables in this study were adapted from existing research, with minor revisions to the wording to suit the context of this study. Specifically, privacy risk was measured by a three item scale from Guo, Zhang & Sun (2016). Physical risk was measured by a two item scale developed by Herrera & Blanco (2011). Social risk was measured by a three item scale from Carlson, O'Cass & Ahrholdt (2015). A sample item is 'People who are important to me would think I am foolish to use online health service'. The three items used to measure social support were adapted from Yan, Wang, Chen & Zhang (2016) who revised scale developed by Xiao (1994). Monetary value was measured by a three item scale from Carlson, O'Cass & Ahrholdt (2015). Three items adapted from Loiacono, Watson & Goodhue (2007) were used to measure convenience value. A sample item is 'Using the online health service would help me save time and efforts'. Utilitarian value was measured by a three item scale adapted from Liang & Xue (2013). The three items measuring online health service usage intention was adapted from Zhang, Guo, Wu, Lai & Vogel (2017) who revised scale developed by Johnston & Warkentin (2010). All items were scored using a five-point Likert scale. The final items used in each scale and the corresponding sources are listed in the Appendix. As the original measurement items were in English and the questionnaires were distributed in China, a back-translation method was used to convert the questionnaire into Chinese.

Sample and Data Collection Procedure

The participants recruited for this study were users of OHS in China. A pilot test was conducted using a convenience sample of 15 students who had used OHS. The feedback obtained in the pilot study was used to refine the survey. An online survey was designed on www.wjx.cn, a professional online survey website in China. The "charged sample" service of www.wjx.cn (a professional online survey website in China) was used and the sample was selected from among 26 million people in www.wjx.cn's sample library. These 26 million people are those who are interested in filling online survey to earn incentives and registered in wjx.com's database. Wjx. com distributed the questionnaire links to registered participants in their database. People who have used OHS were invited to fill the survey. A screen question "whether you have used OHS?" is included. If respondents choose "no" then the questionnaire will end. The data collection last for three days from 17 to19 September, 2018. The respondents were asked to indicate the OHS website they had used. The researchers scrutinized all responses, omitting those with the same answer for all measurement questions to ensure the validity and reliability of the survey results. A dataset of 407 valid responses was obtained. The demographic information is provided in Table 2. There were 42% male and 58% female participants; 48.9% of respondents were aged between 26 and 35. More than 70% of the respondents had a bachelor's degree; 37.1% had an average monthly income between 5,001 and 8,000 CNY.

Table 2. Respondents' demographic profiles (N = 407)

Measure	Items	Frequency	Percent
Gender	Male	171	42
	Female	236	58
Age	18–25	120	29.5
	26–35	199	48.9
	36–45	67	16.5
	>45	21	5.2
Highest education level	High school or below	26	6.4
	Some college	53	13
	Bachelor's degree	294	72.2
	Master's degree or above	34	8.4
Average monthly income (CNY)	<1,000	38	9.3
	1,000–3,000	38	9.3
	3,001–5,000	96	23.6
	5,001–8,000	151	37.1
	>8,000	84	20.6
Length of time using online health service	Less than half a year	49	12
	0.5-1 year	81	19.9
	>1 and <2 years	159	39.1
	>3 and <5 years	97	23.8
	More than 5 ears	21	5.2

Results

Smart PLS 3.0 was employed to analyze the data following a two-step approach. First, the measurement model was tested to evaluate reliability and validity. Second, the structural model was evaluated to test the research hypotheses.

Measurement Model

Convergent validity and discriminant validity were used to evaluate the measurement model. Convergent validity was assessed against three recommended standards: (1) all indicator factor loadings should exceed 0.7; (2) composite reliability (CR) should exceed 0.7; and (3) the average variance extracted (AVE) of each construct should exceed 0.5 (Fornell & Larcker 1981). The results in Table 3 reveal that the loadings of all instrument items were above 0.7, the CR for all constructs ranged from 0.793 to 0.907, and the AVE for all constructs ranged from 0.561 to 0.765, indicating good convergent validity.

To evaluate the discriminant validity, we used multiple techniques. First, we compared the square root of the AVE for each construct to the inter-construct correlations (Chin 1998). The results in Table 4 demonstrate that for each factor, the square root of AVE (the diagonal elements) was larger than its correlation coefficient with other factors. Second, we checked the cross-loading in Table 5 and found that all item loads were higher on their respective construct than on other constructs. These two results indicate that more variance is shared between the corresponding variable and its block of indicators than with other variables representing a different block of indicators (Vatanasaksakul, 2007). Third, we analyzed the Heterotrait-Monotrait Ratio (HTMT), a new criterion for testing discriminant validity in variance-based structural equation modeling proposed by Henseler, Ringle & Sarstedt (2015). According to Henseler, Ringle & Sarstedt (2015), HTMT method offers the best balance between high detection and low arbitrary violation rates. The results in Table 6 confirmed discriminant validity, as all HTMT values were below the threshold of 0.85 (Henseler, Ringle & Sarstedt 2015). In summary, these test results suggest good discriminant validity for all scales.

Given that all the data were collected via a single method (i.e., cross-sectional online survey), there was potential for the responses to be affected by common method bias. In this study, the common method bias was checked using Harman's one-factor test (Harmon 1967). Following this approach, it was found that more than one factor was extracted and the first unrotated factor accounted for only 22.74% of the variance. In addition, there would be a serious problem of common method bias if the correlations among variables were higher than 0.9 (Pavlou & EI Sawy 2006). The results in Table 4 demonstrate that no correlation coefficients were above 0.9. Thus, it can be concluded that common method bias does not influence the results in the current study.

In addition, we assessed multicollinearity using VIFs. The analysis showed that the VIFs ranged from 1.274 to 1.857 (as shown in Table 3), which were all lower than the acceptable cut-off of 3.33 (Genfetelli & Bassellier 2009), implying no significant multicollinearity problem.

Structural Model

The structural model results are presented in Figure 2 below. The R^2 for OHS use intention was 0.444, indicating that 44.4% of the variance of OHS use intention was explained. The Stone-Geisser's Q^2 value was calculated by a blindfolding procedure to judge the predictive power of the model. Q^2 for OHS use intention was 0.260, significantly above 0.15, indicating medium-to-large predictive relevance for the model. In addition, according to Henseler et al. (2014), the standardized root mean square residual (SRMR) was used to evaluate the overall model fit. The value of the SRMR was 0.061, which is below the criterion value of 0.080, indicating a good model fit.

For the inhibitors, we found that privacy risk ($\beta = -0.105$, $p < 0.05$) and social risk ($\beta = -0.170$, $p < 0.01$) had significant and negative effects on OHS use intention. However, physical risk had no significant effect on OHS use intention. Thus, H1 and H3 were supported but H2 was rejected. For the facilitators, social support value ($\beta = 0.258$, $p < 0.01$), convenience value ($\beta = 0.274$, $p < 0.01$),

Table 3. Convergent validity and internal reliability

Constructs and items	Standard Loading	Mean	SD	AVE	CR	VIF
Privacy Risk		3.124	0.923	0.765	0.907	1.435
PR1	**0.878**					
PR2	**0.806**					
PR3	**0.935**					
Physical Risk		2.463	0.966	0.749	0.856	1.857
PHR1	**0.815**					
PHR2	**0.913**					
Social Risk		2.124	0.826	0.671	0.859	1.457
SR1	**0.818**					
SR2	**0.865**					
SR3	**0.771**					
Social Support Value		3.894	0.633	0.578	0.804	1.295
SS1	**0.745**					
SS2	**0.797**					
SS3	**0.738**					
Monetary value		3.642	0.646	0.561	0.793	1.274
MV1	**0.784**					
MV2	**0.746**					
MV3	**0.716**					
Convenience Value		4.080	0.650	0.575	0.802	1.329
CV1	**0.763**					
CV2	**0.787**					
CV3	**0.723**					
Utilitarian value		3.983	0.722	0.669	0.802	1.328
UV1	**0.805**					
UV2	**0.830**					
OHS Use Intention		4.152	0.657	0.635	0.839	
UI1	**0.801**					
UI2	**0.808**					
UI3	**0.781**					

and utilitarian value ($\beta = 0.217$, $p < 0.01$) were found to have positive and significant effects on OHS use intention, while monetary value was found to have no significant effect on OHS use intention. Therefore, H4, H6, and H7 were supported but H5 was rejected.

Regarding the control variables, age ($\beta = 0.099$, $p < 0.05$) and education level ($\beta = 0.113$, $p < 0.01$) were found to have positive impact on OHS use intention, while gender and income were found to have no significant effect on OHS use intention.

Table 4. Correlation matrix

	PR	PHR	SR	SS	MV	CV	UV	UI
PR	***0.875***							
PHR	0.512	***0.865***						
SR	0.300	0.536	***0.819***					
SS	-0.103	-0.194	-0.130	***0.760***				
MV	-0.145	-0.034	-0.038	0.347	***0.749***			
CV	-0.041	-0.168	-0.231	0.304	0.293	***0.758***		
UV	-0.070	-0.164	-0.156	0.359	0.283	0.395	***0.818***	
UI	-0.168	-0.206	-0.295	0.459	0.319	0.486	0.463	***0.797***

Note1: PR = Privacy value; PHR = Physical value; SR = Social risk; SS = Social support value; MV = Monetary value; CV = Convenience value; UV = Utilitarian value; UI = OHS use intention

Note 2: Diagonal lines rendered in boldface show the square root of the AVE of each construct.

Table 5. Item factor loadings and cross-loadings

	PR	PHR	SR	SS	MV	CV	UV	UI
PR1	***0.878***	0.436	0.276	-0.057	-0.107	-0.010	-0.046	-0.124
PR2	***0.806***	0.408	0.188	-0.063	-0.136	0.019	-0.043	-0.061
PR3	***0.935***	0.489	0.289	-0.125	-0.142	-0.071	-0.079	-0.195
PHR1	0.551	***0.815***	0.416	-0.148	-0.065	-0.111	-0.121	-0.144
PHR2	0.374	***0.913***	0.504	-0.184	-0.005	-0.172	-0.159	-0.204
SR1	0.321	0.493	***0.818***	-0.122	-0.048	-0.192	-0.164	-0.235
SR2	0.244	0.454	***0.865***	-0.139	-0.010	-0.200	-0.150	-0.268
SR3	0.170	0.366	***0.771***	-0.053	-0.040	-0.174	-0.062	-0.219
SS1	-0.056	-0.153	-0.044	***0.745***	0.204	0.218	0.226	0.354
SS2	-0.102	-0.158	-0.152	***0.797***	0.279	0.252	0.308	0.374
SS3	-0.076	-0.129	-0.098	***0.738***	0.314	0.224	0.286	0.316
MV1	-0.111	-0.005	-0.018	0.256	***0.784***	0.237	0.256	0.232
MV2	-0.177	-0.082	-0.124	0.242	***0.746***	0.271	0.206	0.243
MV3	-0.035	0.011	0.058	0.280	***0.716***	0.150	0.175	0.241
CV1	-0.030	-0.138	-0.259	0.239	0.245	***0.763***	0.309	0.374
CV2	-0.013	-0.109	-0.138	0.230	0.219	***0.787***	0.309	0.407
CV3	-0.056	-0.141	-0.124	0.224	0.201	***0.723***	0.282	0.309
UV1	-0.023	-0.140	-0.164	0.287	0.213	0.382	***0.805***	0.366
UV2	-0.090	-0.129	-0.093	0.301	0.250	0.270	***0.830***	0.390
UI1	-0.136	-0.196	-0.225	0.391	0.197	0.399	0.361	***0.801***
UI2	-0.188	-0.190	-0.263	0.372	0.316	0.402	0.367	***0.808***
UI3	-0.070	-0.099	-0.216	0.334	0.247	0.353	0.380	***0.781***

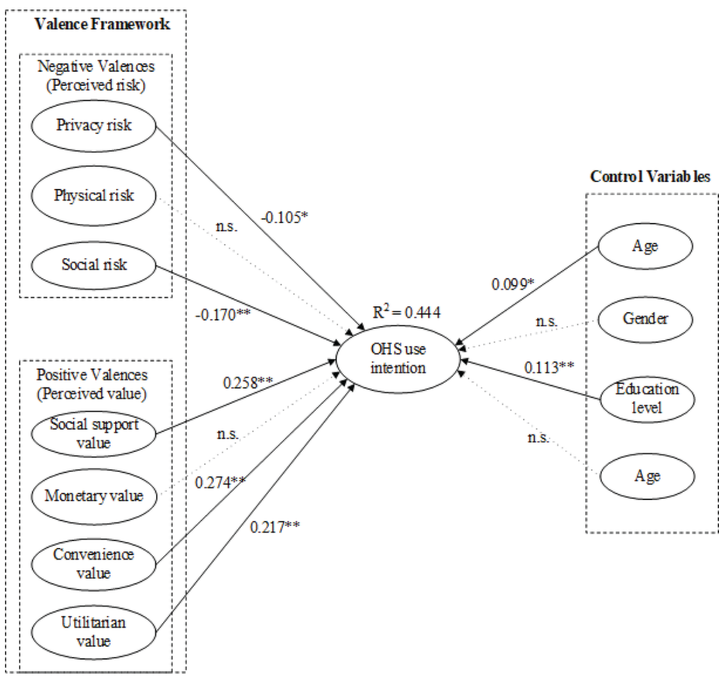
Note: PR = Privacy value; PHR = Physical value; SR = Social risk; SS = Social support value; MV = Monetary value; CV = Convenience value; UV = Utilitarian value; UI = OHS use intention

Table 6. Heterotrait-monotrait ratio

PR	PR	PHR	SR	SS	MV	CV	UV	UI
PHR								
SR	0.685							
SS	0.350	0.741						
MV	0.124	0.290	0.183					
CV	0.209	0.088	0.130	0.561				
UV	0.069	0.253	0.331	0.480	0.471			
UI	0.108	0.275	0.250	0.634	0.511	0.702		
PR	0.179	0.286	0.399	0.679	0.482	0.711	0.771	

Note: PR = Privacy value; PHR = Physical value; SR = Social risk; SS = Social support value; MV = Monetary value; CV = Convenience value; UV = Utilitarian value; UI = OHS use intention

Figure 2. Structural model results



Note: ** $p < 0.01$; * $p<0.05$; n.s.: non-significant

DISCUSSION AND IMPLICATIONS

Discussion of Key Findings

Three major findings emerged from the results. First, this study found that privacy risk and social risk can inhibit individual's OHS use. This finding extends the results from Zhang et al.'s (2017) study. Specifically, they examined the inhibitors of OHS use intention from the perspective of status quo bias by focusing on the effects of traditional health services on adopting the new OHS. We provided more inhibitors of OHS use intention by focusing on the effects of perceived risk. Our results are also in line with Li et al.'s (2018) findings that privacy risk is important for individuals' health information-sharing intentions on social media. However, Li et al. (2018) found that social risk is not significant in influencing users' health information seeking and sharing intentions on social media, which is inconsistent with our results. This may due to the differences of the research context as their study did not cover users' intention to consult doctors online. This finding highlights the role of perceived risks which are deterrents for the use of OHS. OHS providers can then employ strategies to minimize users' perceived risk in order to improve the adoption rate of OHS.

Second, this study found that social support value, convenience value, and utilitarian value are facilitators that can encourage individual OHS use. Although prior research has examined the factors that can facilitate individuals' OHS adoption, most research focuses on the factors of trust, perceived ease of use, perceived usefulness, social support value, and physician/hospital reputation (Mou & Cohen 2014; Zhang, Liu, Deng & Chen 2017). Perceived value is ignored in the literature. This study extends the results of prior studies by demonstrating that convenience value and utilitarian value are significant facilitators of OHS use intention. In addition, the findings are consistent with Li et al. (2018) and Zhang et al. (2018), who found that social support is an important benefit that facilitates individuals' health information-seeking, sharing, and disclosure behavior on online platforms. This finding highlight the current advantages of OHS compared to traditional health services. To attract more users and retain current users, OHS providers can try to offer more utilitarian benefits and social benefits for users.

Thirdly, this study found that physical risk and monetary value do not influence OHS use, which was counter to our expectation. This is likely to be the case because most users generally utilize an OHS to search for health information and communicate with other patients with similar diseases (Li, Wang, Lin & Hajli 2018). Only a minority of users consult physicians online to seek a diagnosis. Therefore, physical risk is not a concern. Further, in China, when patients have serious health concerns, they prefer to see a physician in person (Li, Wang, Lin & Hajli 2018). This also explains why monetary value is not important for OHS use intention, because patients in China may prefer to seek a more credible treatment service despite the greater cost. This result further indicates that OHS providers can utilize more new technologies to attract users to use consulting service via OHS platforms. If these services are credible, users care less about the cost of these services. Further, more services can be developed on OHS platforms to attract users.

Finally, our research also indicates the effects of the control variables on the OHS use intention. Education level has positive effects on OHS use intention, indicating that highly educated participants are more likely to adopt OHS. This finding also supports Zhang, Guo, Wu, Lai & Vogel (2017)'s results. However, age was found to be positively related to OHS use intention, which contrasts with Zhang, Guo, Wu, Lai & Vogel (2017)'s finding. This may be because the participants in our study were relatively young, with 95% aged below 45 years. Since older people have more health problems, they are more likely to adopt OHS. Gender and income have no impact on OHS use intention. This may also due to that majority of the services users adopted in OHS platforms are free. Users mainly use these platforms to search information and sharing information with each other.

Implications for Research and Practice

This study has several theoretical implications. First, it is among the first to apply a valence framework to examine user behavior in the OHS context, extending its application scope. The valence framework explains the consumer decision-making process. Through global literature retrieval in the IS field, we found that the valence framework has been employed in the context of online shopping (Kim, Ferrin & Rao 2008), mobile payments (Gao & Waechter 2017), and health information-sharing on social media (Li, Wang, Lin & Hajli 2018). However, it has seldom been used to explain user behavior in the OHS context. By applying the valence framework in this context, we found that users evaluate both the positive and negative valences when adopting OHS. Future research investigating user behavior in the OHS context could employ this framework to explore other facilitators and inhibitors that influence users during the OHS adoption process.

Second, previous studies on OHS have focused on factors that can facilitate user adoption behavior. However, the factors that inhibit the OHS adoption have been largely ignored. This study is among the first to systematically examine both facilitating and inhibiting factors. The positive valence factors include social support, convenience value, and utilitarian value, while the negative valence factors include privacy risk and social risk. These findings complement current research that uses the technology acceptance model, the theory of reasoned action, and the theory of planned behavior to examine technology or technology-based service adoption. Future research examining technology or technology-based service adoption could also consider both facilitators and inhibitors to provide a more comprehensive understanding of user technology adoption behavior.

This study also has several practical implications for online platforms offering OHS. First, given that users are greatly concerned about privacy and social risk when making the decision to adopt OHS, online platforms offering OHS can provide privacy training to employees that access user data to minimize users' privacy risk. Such platforms can also employ security protection mechanisms to ensure that users' private information is not hacked. In addition, these platforms could consider not collecting unnecessary personal information about users. For instance, users could register anonymously without identity information (e.g., identity card number) and contact information (e.g., phone number) since this information is not necessary for medical consultation. With higher levels of anonymity, users may feel lower levels of perceived privacy risk. To minimize users' social risk, OHS platform operators can engage in more marketing to ensure more people understand the value of using OHS. Incentives such as reputable rewards and answer ratings could be employed to help professionals to build their reputation, which is also helpful building a platform's reputation. Reputable physicians could also be invited to provide consultant services on the platform to help build platform reputation. When OHS are widely accepted by patients, users will feel less pressure when adopting them.

In addition, social support, convenience value, and utilitarian value can encourage users to adopt OHS. To improve users' perceived social support, OHS platforms can help patients with similar health concerns to create groups on online platforms to communicate with each other, which can provide social support for patients. Users who are active in sharing health-related knowledge and replying to other patients' enquiries could be rewarded. To improve the convenience value, online platforms offering OHS should provide information in more user-friendly formats. To improve utilitarian value, online platforms should employ more qualified physicians who can effectively solve or provide advice for patients with health problems. The information shared by other patients on the online platform should also be screened by qualified physicians to improve the credibility of the information and further improve the utilitarian value of the OHS.

LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, we collected data using a cross-sectional approach, which may weaken the justification for the direction of the hypotheses. Future research could utilize a longitudinal approach to collect data at multiple time points to verify causality among the variables. Second, this study focused on the inhibitors and facilitators of OHS use intention. The inhibitors privacy risk, social risk, physical risk, and the facilitators of social support, monetary value, convenience value, and utilitarian value are included in the model. There are other factors that may influence OHS use intention that should be explored in future research. Third, the data were collected in China only. Issues related to culture and healthcare regulations may influence the results and decrease the generalizability of our study. Future research might replicate this study based on data collected in other cultural contexts to improve the generalizability of the results.

Conflict of Interest

All authors have no potential conflicts of interest to disclose.

ACKNOWLEDGMENT

This work was supported by Young Scientists Fund from Ministry of Education in China Project of Humanities and Social Sciences [grant number 20YJC630163] and Fundamental Research Funds for the Central Universities [grant number NS2020062].

REFERENCES

Al-Debei, M. M., & Al-Lozi, E. (2014). Explaining and predicting the adoption intention of mobile data service: A value-based approach. *Computers in Human Behavior*, *35*, 326–338. doi:10.1016/j.chb.2014.03.011

Analysys. (2018). *Online health service annual report of China*. Retrieved from http://www.analysys.cn

Atanasova, S., Kamin, T., & Petric, G. (2018). The benefits and challenges of online professional-patient interaction: Comparing views between users and health professional moderators in an online health community. *Computers in Human Behavior*, *83*, 106–118. doi:10.1016/j.chb.2018.01.031

Bansal, G., Zahedi, F., & Gefen, D. (2010). The impact of personal dispositions on information sensiticity, privacy concern and trust in disclosing health information online. *Decision Support Systems*, *49*(2), 138–150. doi:10.1016/j.dss.2010.01.010

Bao, Y., Hoque, R., & Wang, S. (2017). Investigating the determinants of Chinese adult children's intention to use online health information for their aged parents. *International Journal of Medical Informatics*, *102*, 12–20. doi:10.1016/j.ijmedinf.2017.01.003 PMID:28495340

Bernhardt, J. M., Lariscy, R. A., Parrott, R. L., Silk, K. J., & Felter, E. M. (2002). Perceived barriers to internet-based health communication on human genetics. *Journal of Health Communication*, *7*(4), 325–340. doi:10.1080/10810730290088166 PMID:12356290

Carlson, J., O'Cass, A., & Ahrholdt, D. (2015). Assessing customers' perceived value of the online channel of multichannel retailers: A two country examination. *Journal of Retailing and Consumer Services*, *27*, 90–102. doi:10.1016/j.jretconser.2015.07.008

Chang, Y.-W., Hsu, P.-Y., Wang, Y., & Chang, P.-Y. (2019). Integration of online and offline health services: The role of doctor-patient online interaction. *Patient Education and Counseling*, *102*(10), 1905–1910. doi:10.1016/j.pec.2019.04.018 PMID:31279612

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In Modern methods for business research. Lawrence Erlbaum Associates, Inc.

Cobb, S. (1976). Social support as a moderator of life stress. *Psychosomatic Medicine*, *38*(5), 300–314. doi:10.1097/00006842-197609000-00003 PMID:981490

Cocosila, M., & Trabelsi, H. (2016). An integrated value-risk investigation of contactless mobile payments adoption. *Electronic Commerce Research and Applications*, *20*, 159–170. doi:10.1016/j.elerap.2016.10.006

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Computer Studies*, *59*(4), 451–474. doi:10.1016/S1071-5819(03)00111-3

Fisher, J., Burstein, F., Lynch, K., & Lazarenko, K. (2008). Usability + usefulness = trust: An exploratory study of Australian health web sites. *Internet Research*, *18*(5), 477–498. doi:10.1108/10662240810912747

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *JMR, Journal of Marketing Research*, *19*, 440–452. doi:10.1177/002224378201900406

Gao, L. & Waechter, K. A. (2017). Examining the role of initial trust in user adoption of mobile payment services: An empirical investigation. *Information Systems Frontiers, 19*, 525-548.

Genfetelli, R. T., & Bassellier, G. (2009). Interpretation of formative measurement in information systems research. *Management Information Systems Quarterly*, *33*(4), 689–707. doi:10.2307/20650323

Graffigna, G., Barello, S., Bonanomi, A., & Riva, G. (2017). Factors affecting patients' online health information-seeking behaviours: The role of the patient health engagement (PHE) model. *Patient Education and Counseling*, *100*(10), 1918–1927. doi:10.1016/j.pec.2017.05.033 PMID:28583722

Guo, X., Zhang, X., & Sun, Y. (2016). The privacy-personalization paradox in mhealth services acceptance of different age groups. *Electronic Commerce Research and Applications*, *16*, 55–65. doi:10.1016/j.elerap.2015.11.001

Hajli, M., Bugshan, H., Lin, X., & Featherman, M. (2013). From e-learning to social learning - a health care study. *European Journal of Training and Development*, *37*(9), 851–863. doi:10.1108/EJTD-10-2012-0062

Harmon, H. H. (1967). *Modern factor analysis*. University of Chicago Press.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Ronkko and Evermann (2013). *Organizational Research Methods*, *17*(2), 182–209. doi:10.1177/1094428114526928

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. doi:10.1007/s11747-014-0403-8

Herrera, C. F., & Blanco, C. F. (2011). Consequences of consumer trust in PDO food products: The role of familiarity. *Journal of Product and Brand Management*, *20*(4), 282–296. doi:10.1108/10610421111148306

Jiang, L., Yang, Z., & Minjoon, J. (2013). Measuring consumer perceptions of online shopping convenience. *Journal of Service Management*, *24*(2), 191–214. doi:10.1108/09564231311323962

Johnston, A. C., & Warkentin, M. (2010). Fear appeals and information security behaviors: An empirical study. *Management Information Systems Quarterly*, *34*(3), 549–566. doi:10.2307/25750691

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, *44*(2), 544–564. doi:10.1016/j.dss.2007.07.001

Kim, H. W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. *Decision Support Systems*, *43*(1), 111–126. doi:10.1016/j.dss.2005.05.009

Li, Y., Wang, X., Lin, X., & Hajli, M. (2018). Seeking and sharing healthinformation on social media: A net valence model and cross-cultural comparison. *Technological Forecasting and Social Change*, *126*, 28–40. doi:10.1016/j.techfore.2016.07.021

Liang, H., & Xue, Y. (2013). Online health information use by disabled people: The moderating role of disability. *Proceedings of the 34th International Conference on Information Systems*.

Lin, J., Wang, B., Wang, N., & Lu, Y. (2014). Understanding the evolution of consumer trust in mobile commerce: A longitudinal study. *Information Technology Management*, *15*(1), 37–49. doi:10.1007/s10799-013-0172-y

Loiacono, E., Watson, R., & Goodhue, D. (2007). Webqual: An instrument for consumer evaluation of websites. *International Journal of Electronic Commerce*, *11*(3), 51–87. doi:10.2753/JEC1086-4415110302

Lu, Y., Yang, S., Chau, P. Y. K., & Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management*, *48*(8), 393–403. doi:10.1016/j.im.2011.09.006

Maloneykrichmar, D., & Preece, J. (2005). A multilevel analysis of sociability, usability, and community dynamics in an online health community. *ACM Transactions on Computer-Human Interaction*, *12*(2), 201–232. doi:10.1145/1067860.1067864

Mano, R. S. (2014). Social media and online health services: A health empowerment perspective to online health information. *Computers in Human Behavior*, *39*, 404–412. doi:10.1016/j.chb.2014.07.032

Mitchell, V. W. (1999). Consuer perceived risk: Conceptualizations and models. *European Journal of Marketing*, *33*(1-2), 163–195. doi:10.1108/03090569910249229

Mitchell, V. W., & Greatorex, M. (1988). Consumer risk perception in the UK wine market. *European Journal of Marketing*, *22*(9), 5–15. doi:10.1108/EUM0000000005296

Mou, J., & Cohen, J. F. (2014). *A longitudinal study of trust and perceived usefulness in consumer acceptance of an eservice, the case of online health services*. The 2014 Pacific Asia Conference on Information Systems, Chengdu, China.

Mou, J., Shin, D.-H., & Cohen, J. (2017). Understanding trust and perceived usefulness in the consumer acceptance of an e-service: A longitudinal investigation. *Behaviour & Information Technology*, *36*(2), 125–139. doi:10.1080/0144929X.2016.1203024

O'Brien, H. L. (2010). The influence of hedonic and utilitarian motivations on user engagement: The case of online shopping experience. *Interacting with Computers*, *22*(5), 344–352. doi:10.1016/j.intcom.2010.04.001

Overby, J. W., & Lee, E. J. (2006). The effects of utilitarian and hedonic online shopping value on consumer preference and intentions. *Journal of Business Research*, *59*(10), 1160–1166. doi:10.1016/j.jbusres.2006.03.008

Pavlou, P. A., & Sawy, E. I. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, *17*(3), 198–227. doi:10.1287/isre.1060.0094

Peters, P. J., & Tarpey, L. X. (1975). A comparative analysis of three consumer decision strategies. *The Journal of Consumer Research*, *2*(1), 29–37. doi:10.1086/208613

Porter, C. E., & Donthu, N. (2006). Using the technology acceptance model to explain how attitudes determine internet usage: The role of perceived access barriers and demographics. *Journal of Business Research*, *59*(9), 999–1007. doi:10.1016/j.jbusres.2006.06.003

Qu, B., Li, X., Liu, J., & Mao, J. (2012). Analysis of the current situation regarding the aging rural population in China and proposed countermeasures. *Population Health Management*, *15*(3), 181–185. doi:10.1089/pop.2011.0033 PMID:22401147

Rezaei, S., & Ghodsi, S. S. (2014). Does value matters in playing online game? An empirical study among massively multiplayer online role-playing games (MMORPGs). *Computers in Human Behavior*, *35*, 252–266. doi:10.1016/j.chb.2014.03.002

Roselius, T. (1971). Consumer rankings of risk reduction methods. *Journal of Marketing*, *35*(1), 56–61. doi:10.1177/002224297103500110

Sweeney, J. C., Soutar, G. N., & Johnson, L. W. (1999). The role of perceived risk in the quality-value relationship: A study in retail environment. *Journal of Retailing*, *75*(1), 77–105. doi:10.1016/S0022-4359(99)80005-0

Venkatesh, V., Speier, C., & Morris, M. G. (2002). User acceptance enablers in individual decision making about technology: Toward an integrated model. *Decision Support Systems*, *33*(2), 297–316.

Xiao, L., Guo, Z., & D'Ambra, J. (2017). Analyzing consumer goal structure in online group buying: A means-end chain approach. *Information & Management*, *54*(8), 1097–1119. doi:10.1016/j.im.2017.03.001

Xiao, L., Guo, Z., D'Ambra, J., & Fu, B. (2016). Building loyalty in e-commerce: Towards a multidimensional trust-based framework for the case of China. *Program-Electronic Library & Information Systems*, *50*(4), 431–461. doi:10.1108/PROG-04-2016-0040

Xiao, L., & Li, Y. (2019). Examining the effect of positive online reviews on consumers' decision making: The valence framework. *Journal of Global Information Management*, *27*(3), 159–181. doi:10.4018/JGIM.2019070109

Xiao, N., Sharman, R., Rao, H. R., & Upadhyaya, S. (2014). Factors influencing online health information search: An empirical analysis of a national cancer-related survey. *Decision Support Systems*, *57*, 417–427. doi:10.1016/j.dss.2012.10.047

Xiao, S. (1994). Theoretic foundation and research application about the social support rating scale. *The Journal of Clinical Psychiatry*, *4*(2), 98–100.

Yan, Z., Wang, T., Chen, Y., & Zhang, H. (2016). Knowledge sharing in online health communities: A social exchange theory perspective. *Information & Management*, *53*(5), 643–653. doi:10.1016/j.im.2016.02.001

Yang, H., Guo, X., Wu, T., & Ju, X. (2015). Exploring the effects of patient-generated and system-generated information on patients' online search, evaluation and decision. *Electronic Commerce Research and Applications*, *14*(3), 192–203. doi:10.1016/j.elerap.2015.04.001

Zeithaml, V. A. (1988). Consumer perceptions of price, quality and value: A means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2–22. doi:10.1177/002224298805200302

Zhang, X., Guo, F., Xu, T., & Li, Y. (2020). What motivates physicians to share free health information on online health platforms. *Information Processing & Management*, *57*(2), 57. doi:10.1016/j.ipm.2019.102166

Zhang, X., Guo, X., Wu, Y., Lai, K., & Vogel, D. (2017). Exploring the inhibitors of online health service use intention: A status quo bias perspective. *Information & Management*, *54*(8), 987–997. doi:10.1016/j.im.2017.02.001

Zhang, X., Liu, S., Chen, X., Wang, L., Gao, B., & Zhu, Q. (2018). Health information privacy concerns, antecedents, and information disclosure intention in online health communities. *Information & Management*, *55*(4), 482–493. doi:10.1016/j.im.2017.11.003

Zhang, X., Liu, S., Deng, Z., & Chen, X. (2017). Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users. *Computers in Human Behavior*, *75*, 797–810. doi:10.1016/j.chb.2017.06.028

Zhang, Y., Sun, Y., & Kim, Y. (2017). The influence of individual differences on consumer's selection of online sources for health information. *Computers in Human Behavior*, *67*, 303–312. doi:10.1016/j.chb.2016.11.008

Zhu, X., & Bao, Z. (2018). Why people use social networking sites passively: An empirical study integrating impression management concern, privacy concern, and sns fatigue. *Aslib Journal of Information Management*, *70*(2), 158–175. doi:10.1108/AJIM-12-2017-0270

APPENDIX

Table 7. Instrument items

Constructs		Measurement Items
Privacy risk (Guo, Zhang & Sun 2016)	PR1	If I use the online health service, I would lose control over the privacy of my personal information
	PR2	My personal information would be less confidential if I use online health service
	PR3	Using online health service would lead to a loss of privacy for me because my personal information would be used without my permission
Physical risk (Herrera & Blanco 2011)	PHR1	I am afraid using online health service will be unsafe for me or my family
	PHR2	I am afraid using online health service may affect my health
Social risk (Carlson, O'Cass & Ahrholdt 2015)	SR1	People who are important to me would think I am foolish to use online health service
	SR2	using online health service would lead to a loss of status for me because my friends and relatives would think less highly for me
	SR3	Using online health service would harm the way others think of me
Social support (Yan, Wang, Chen & Zhang 2016)	SS1	In the online health communities, I pour out my trouble and feel relaxed
	SS2	In the online health communities, I get some understanding, help or supports from other participants in the community
	SS3	In the online health communities, I get comfort and care from other participants in the community
Monetary value (Carlson, O'Cass & Ahrholdt 2015)	MV1	The pricing policies in the online health communities are fair
	MV2	The online health communities provides me with consistent and accurate pricing policies
	MV3	The pricing policy in the online health communities are more beneficial for me than traditional offline health service
Convenience value (Loiacono, Watson & Goodhue 2007)	CV1	Using the online health service would help me save time and efforts
	CV2	It is easier to use the online health service
	CV3	I think using online health service does not require a lot of mental effort
Utilitarian value (Liang & Xue 2013)	UV1	Online health services increase my knowledge of my personal health conditions
	UV2	Online health services help to relieve stresses about my new symptoms or my worries about new symptoms
Online health service usage intention (Zhang, Guo, Wu, Lai & Vogel 2017)	UI1	I intend to transit to online health services in the future when needed
	UI2	I predict I will use online health services in the future when needed
	UI3	I plan to use online health services in the future when needed

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