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Factors Affecting User Intention to Pay via Online Medical Service Platform:

Role of Misdiagnosis Risk and Timeliness of Response

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ABSTRACT

This study investigates key factors influencing the users' intention to pay for online medical service via the online platform performance and trust. A data sample of 312 is gathered via a questionnaire survey, with analysis performed via partial least squares structural equation modeling. Results portray a new perspective within the context of internet usage research for online medical service platform adoption and use behaviors. Briefly, the information quality, system quality, and convenience of the platform are found to affect the perceived benefit of users significantly. Among other findings, users' perceived reliability of the platform also positively affects doctor reliability and the users' intention to pay whereas doctor reliability positively affects the users' intention to pay. Moreover, the misdiagnosis risk positively regulates the relationship between the users' trust tendency and doctor reliability. Finally, the timeliness of the response of the platform also moderates positively the relationship between doctor reliability and the users' intention to pay.

KEYWORDS

Intention to Pay, Platform Performance, Risk, Trust

1. INTRODUCTION

With diffusing Internet technology, people in China, who have often been challenged with a dire shortage of medical resources, may now effectively tend to their growing medical needs via the online medical service platform. Globally, the emergence of online medical treatment has also broadened the channels of interaction between patients and doctors, particularly in today's era of the COVID-19 pandemic. Specifically, within China, online medical services provide patients with additional medical information and an alternative treatment option by maximizing existing resources while potentially reduce consultational and logistic costs.

The primary users of the online medical service platform have been patients. In fact, patients' perception and their intention to pay (ITP) for the online medical service platform can significantly impact on the current development, future adoption and long-term sustainability of the online medical service model. Developers of such online platform(s) need then to pay attention to key factors influencing patients' adoption of the new modality. Clinicians (doctors) form a secondary group of users. Accordingly, a well-designed platform must incorporate both easy-to-use and easy-to-learn

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features that would guide both patients and clinicians on how best to engage with each other when interacting in online medical media so as to improve communications and clinical work efficiencies and effectiveness.

Over the years, the development of online healthcare services has been slow, hampered by a lack of online applications and services to facilitate timely interactions between patients and medical professionals. With the growth of innovative platforms, patients can now get to improve their health literacy, and they can also now increase their social supports and mobilize other resources for health-related issues. As well, the obligations, responsibilities, and authorities of the medical professionals are also beginning to be standardized considerably via use of these platforms (S. Atanasova, Kamin, & Petric, 2017; Ringle, Sarstedt, & Straub, 2012). Yet, existing studies tend to focus on the users' health information literacy, their perceived value of online medical platform, their information sharing behaviors and their concerns over health anxiety when using such platforms (McMullan, Berle, Arnáez, & Starcevic, 2019) with little attempts, if any, to pursue insights into key factors affecting users' ITP, thereby sustaining the use of such online medical platform.

Hence, to overcome the need for more research on the sustainability of online medical service platforms, a research model is constructed to examine key factors affecting users' ITP. It is hoped that this investigation will not only offer critical insights into users' behaviors for sustained use of such online medical platforms, but also practical guidelines on how best to design and develop such platforms.

The rest of this paper is organized as follows. Section 2 lays out the background on related works linked to online medical platform and services. Section 3 highlights the research model and hypotheses by drawing on our past knowledge of the popular technology acceptance model (TAM) and the perceived risk theory (PRT) to explore the key factors influencing patients' ITP construct. Section 4 shifts focus to methods, including the data sampling and collection efforts as well as the rationale for applying certain data analytic approaches. Section 5 offers insights into how the research data should be aggregated and interpreted whereas Section 6 provides several concluding remarks, including potential limitations and future works.

2. RESEARCH BACKGROUND

Over the years, owing to its readily availability and convenient accessibility, the Internet has grown to become a favored source for seeking medical information among laypersons who may often have only limited health information literacy. Worldwide, about 4.5% of all active Internet searches has been purported to be for medical-related information and/or services. Fox & Duggan issued a 2013 Pew Research Center survey report to show that almost 35% of adults in the United States (US) use the Internet to seek health diagnosis, out of which half of them will trust the professional diagnosis and treatment means they have gathered from the Internet (S & M, 2013).

2.1 Online Medical Services

Online medical services generally entail new Internet-based applications in the medical services offered by third-party payers, for example, the insurers, government and employers vis-à-vis their subscribing insurers.

Online medical services often include, but may not be limited to, medical information query, online disease consultation, remote consultation and telemedicine and/or other forms of e-health services. (Farnan, Sulmasy, & Chaudhry, 2013). In China, the potential market for online medical services is estimated to soon reach 164.8 billion RMB (YiGuan, 2019). An underlying rationale here is that online health information may be considered to offer a low-cost but highly potential means of boosting one's quality of personal health care. Moreover, the growing availability of such servicing may also be useful to promote or guide one's preventive or changing healthy lifestyle behaviors (Park, Hartzler, Huh, Hsieh, & Pratt, 2016).

2.2 Information Sharing Via Online Medical Platform

With the COVID-19 pandemic and as people are alerted to become increasingly more aware on issues about their health and general wellbeing, online healthy communities based on user-generated content have emerged and grown rapidly, resulting in an even greater number of users who are actively sharing health information via online communities (Tanis, Hartmann, & te Poel, 2016). Advances in health information technology (health IT) and the growth of such online communities have in turn affected the online communication channels between patients and providers.

Many online communities have become convenient hot spots for aiding patients to communicate and seek social support from those having similar health-related interests or concerns, for example, COVID-19 issues. Importantly, these online communities provide patients with quick and easy access points if and whenever social support may be needed. These community websites can also be beneficial to assist patients with both their physical and mental health needs. Users' community awareness, privacy disclosure and protection awareness, and the contribution of preventive health knowledge can significantly influence the knowledge contributions of such online communities.

Four roles are generally present among users interacting within the context of an online health community: caregivers, opportunists, scientists, and adventurers (Huh et al., 2016; H. Wu & Lu, 2017). The knowledge of online health communities may thus be subdivided into general (public) and specific (private) knowledge. A sense of self-worth, members' sense of social support, and the reputational improvement are expected to have positive impacts on both general and specific knowledge sharing (Swanson, Kim, Lee, Yang, & Lee, 2020; Zaggl, 2017). However, self-esteem has been purported to have a negative impact on specific knowledge sharing but a positive impact on general knowledge sharing(E.-J. Lee & Jang, 2010) . Similarly, execution costs have been found to negatively impact on general knowledge sharing, whereas cognitive costs are expected to negatively impact on specific knowledge sharing(Yu, Lan, & Zhao, 2018; Z. Zhang, Song, & Song, 2020) . Finally, while personal interests can promote knowledge sharing, the execution costs and cognitive costs may hinder such knowledge sharing (Yan, Wang, Chen, & Zhang, 2016).

Today, many healthcare providers encourage their patients to engage in online health communities if and when they are seeking to improve their own health behaviors and/or to afford them with needed social supports as the information provided by most such online medical websites is often deemed to be generally accurate. Nevertheless, Cisu, et al. (2019) argue that information contained in the medical professional websites is typically more accurate than that provided by commercial websites. More importantly, the quality of information provided in the online healthcare community would affect service quality, which would further affect users' satisfaction(Hajli, 2014). Consumer needs for health information and both the tangible and intangible attributes of available and accessible health information afforded to consumers should be considered as important antecedents of accepting online health communication via social networking sites (J. W. Lee, 2017).

Based on reported observations of the extant literature, male professional users, when issuing health information, tend to use more medical terms than female users; in contrast, female users are more inclined to receive emotional supports compare to their male counterparts (Rosenberg, Mano, & Mesch, 2020). As well, female users show higher anxiety and greater sadness than male users, The centrality of male users in their focus on a friendship network is higher than that of females (Liu, Sun, & Li, 2018).

Presently, research on what motivates the knowledge sharing behavior of online healthy communities has emerged. Reciprocity and altruism appear to have positive effects on the willingness of knowledge sharing among health professionals and ordinary users . Reputation and knowledge self-efficacy are found to have a greater impact on health professionals' willingness to share knowledge than ordinary users; specifically, reciprocity, altruism, and empathy strongly influence health professionals' willingness to share knowledge (X. Zhang, Liu, Deng, & Chen, 2017). Cognitive beliefs will also affect online health information sharing. From an epistemological perspective, participants with weaker cognitive abilities are more likely to share online health information than users with stronger cognitive abilities, and those with stronger cognitive abilities are more likely to share text information instead of information in the form of an image (Chua & Banerjee, 2017).

Unlike the face-to-face (ftf) communication between patients and professional doctors, who can often provide information cues and emotional support for satisfying the health needs of their patients, the online health community is limited by the nature of its virtual presence. The limitations of the network and communication infrastructures are the main obstacles that affect the online communication between patients and professional doctors (Sara Atanasova, Kamin, & Petrič, 2018). Health information privacy issues can also have a significant impact on the patients' willingness to disclose sensitive health information. Privacy issues are negatively affected by perceived efficacy and self-efficacy but positively influenced by perceived vulnerability and severity (P. Liang, Zhang, Kang, & Ren, 2019). Different health conditions have a significant impact on health information disclosure (X. Zhang et al., 2018).

2.3 Health Information Literacy

Health information literacy refers to the extent in which an individual is capable of acquiring, processing, and understanding basic health information for the purpose of making relevant health-related decisions (IOM, 2004).

(Guy, Jean-Nicolas, Claude, & Marc, 2009) argue that the use of the Internet as a source of health information is directly related to three main factors: gender, age and the individual's perceived ability to understand, interpret and use the available online medical information. With rapid health data digitization, the volume of online information about health and disease has increased dramatically, and health literacy plays a key role in the correct selection and use of massively available and accumulating information. Patients must have a reasonable level of health knowledge to sort out accurate and trustworthy information (Aydın, Kaya, & Turan, 2015). While there has been an increasing number of users who can access and understand health information via the Internet, people with higher e-health knowledge and skills will certainly tend to be more effective in their online information search strategies than those with lower e-health knowledge and skills (Quinn, Bond, & Nugent, 2017).

Reference credibility is key in determining the value and validity of scientific information; in this context, the health literacy of both the health information users as well as the providers appears to be the most critical differentiating factor. For example, the literacy of health information providers is important in influencing the validity of the empirical information offered (Lederman, Fan, Smith, & Chang, 2014). An effective assessment of online health information requires a hybrid approach that combines both quantitative and qualitative assessments, and the assessment tool should be selected based on the functional characteristics and compatibility of the target information. Readability tools have also been widely used to evaluate online health information, and the effectiveness of online health information via emotional analytic tools is also becoming increasingly common (Beaunoyer, Arsenault, Lomanowska, & Guitton, 2017). Yet, the credibility of online health information sources appears to have no significant effect on perceived information credibility(Ma & Atkin, 2017; Machackova & Smahel, 2018) . When user-generated online health information is posted on a common website, high-confidence information sources are significantly correlated with high-perceived information credibility (Ma & Atkin, 2017).

Demography also plays a key role to define users' preferences for the type of health information needed publicly. Understanding demography would therefore assist the government in generating the desired health information to meet the needs of individual users and communities, potentially improving medical conditions, and satisfying the individualized online experiences of the users, thereby providing targeted medical resources in combination with the interests of different segments of the population (Nigam, Johnson, Wang, & Chawla, 2019). Patients' involvement would affect the ability to search and manage online health information (Graffigna, Barello, Bonanomi, & Riva, 2017). Patients use different criteria to assess scientific and empirical information. Patients with higher education and greater access to medical services have a higher rate of online medical enquiries than those with lower education and more limited access to medical services (Waring, McManus, Amante, Darling, & Kiefe, 2018).

The Internet has become an important source for the elderly to search for health information. The elderly learn about diseases, drugs, treatments, as well as healthy lifestyles by searching for health information online. Surprisingly, elderly people have a generally positive attitude toward health information retrieval. In task search performance, education level and network search ability are significantly correlated. Health status, familiarity with the Internet, and credibility of online health information are the main factors that affect health information searches (D. Wu & Li, 2016). Health status, trust in information, lack of access to the Internet, and attitudes of health professionals all influence the usefulness of the available online health information. Low trust, economic barriers, lack of understanding of the Internet, and low health knowledge levels seriously affect the ability to access online health information for the elderly (Waterworth & Honey, 2018).

Finally, the evaluation of online health information by teenagers mainly includes an evaluation based on the website's name and reputation, an evaluation according to the first impression of the website, and an evaluation of the website's content, with the typical lack of well thought out evaluation strategies (Freeman, Caldwell, Bennett, & Scott, 2018).

3. RESEARCH MODEL AND HYPOTHESES

Davis (1989) proposes the technology acceptance model (TAM), which mainly draws upon the theory of reasoned action (TRA) to study users' acceptance of information technologies. The original purpose of the proposed TAM is to explain the decisive factors that are widely accepted by technology users. The TAM posits that the individual behaviors in the use of information systems (IS) are determined by their intention to use, and such an intention is further determined by the system's perceived usefulness (PU) and perceived ease of use (PEU).

Over the years, TAM has been successfully applied across a variety of technology use domains to confirm its value (Chintalapati & Daruri, 2017; Scherer, Siddiq, & Tondeur, 2019; B. Wu & Chen, 2017; Yoon, 2018). As such, TAM can explain the problem of patients' ITP in online medical environment (Ahmad, Zhou, & Koru, 2014). More recently, online medical service has become popularized, connecting patients, particularly young people, with medical professionals as these younger consumers see online medical platforms to have a highly PU and ease of use ratings. This article will combine the characteristics of the online medical systems and patients' characteristics, and will also consider the impact of various external variables, for example, the online platform information quality (IQ), the platform system quality (SQ), and the platform convenience vis-à-vis the intention to purchase online medical service(s) or ITP.

3.1 Perceiver Risk Theory (PRT) and Perceived Service Quality Theory (PSQT)

Aside from technological factors, perceived risk (P-risk), which is commonly thought of as potential or lingering uncertainties regarding the possible negative consequences of using a product or service (Featherman & Pavlou, 2003), is also posited as a prominent barrier to consumer acceptance of e-services. A large number of scholars have studied the P-risk construct and some have their own definition of P-risk.

Sun (2014), for example, defines P-risk as an inhibitory effect on purchasing behavior due to the presence of expected loss in the context of shopping behavior. Mitchell and Laura (1999) argue that consumers tend to reduce their P-risk rather than maximize their perceived benefits (PB); in other words, P-risk is more powerful in the interpretation of consumer buying behavior than PB. More recently, some researchers have used the P-risk theory (PRT) to construct the model in the study of influencing factors on consumer online shopping (Chopdar, Korfiatis, Sivakumar, & Lytras, 2018; Davari, Iyer, & Rokonuzzaman, 2016; Marriott & Williams, 2018; Yang, Sarathy, & Lee, 2016). Still, the lack of technology use model in P-risk may be due to the complexity of the P-risk concept. Accordingly, the interpretation of past study results has been controversial in this field, and the P-risk measurement model still needs to be further developed, demanding substantive empirical testing and research.

Owing to the stated reasons, this paper combines the TAM and PRT to explore key factors affecting the patients ITP. Specifically, a theoretical framework is developed to explain the ITP for online medical service. Structural equation modeling (SEM) is then employed for parameters estimation and testing of the proposed hypotheses. It is argued that the study results will be useful for our understanding of the behaviors of patient use of online medical service so as to better promote the IS development to support online medical service(s).

The effectiveness of IS depends on its quality which in turn is determined by such IS characteristics as functionality, reliability, usability, and portability (Bevan, 2001). Poor usability reduces the use of IS and hinders its acceptance by users. (Cresswell & Sheikh, 2013). One recent socio-technical model shows that technical factors (e.g., PU, PEU, versatility, and communication), social factors (e.g., health care quality, awareness of electronic health, and openness), management factors (e.g., hospital management, doctors' support, and government motivation), and psychological factors (e.g., e-health literacy, computer self-efficacy, and computer anxiety) can all have significant effects on the users' willingness to adopt online medical care (Razmak, Belanger, & Farhan, 2018). IT facilitation factors and health incentives can also strongly influence patients' online health information search behaviors.

The online health information search behavior of patients may be described from the frequency of online health information search, the diversity of available and accessible online health information, and preferences in online search behaviors. The accessibility of online services and trust in online health information can further affect the frequency of online health information searches. The communication quality between patients and doctors can also have an impact on the diversity of online health information and the online search preferences (Xiao, Sharman, Rao, & Upadhyaya, 2014).

Based on past study results, we propose and speculate on the following hypotheses:

H_1: Platform information quality (IQ) will significantly (& positively) affect user's perceived benefit (PB).

PB refers to the perception of the positive consequences that are caused by a specific action (El-Masri & Tarhini, 2017; Oliveira & Martins, 2011).

According to (Rieh, 2002), the quality of information or IQ is the degree to which individuals consider the message as current, precise, good and useful. Low IQ increases information-processing costs, time, and effort due to reading of irrelevant and useless messages (Gu, Konana, Rajagopalan, & Chen, 2007). If one is uncertainty about the IQ of a massive amount of online health information, it would be difficult, if not impossible, to retrieve the correct information in a timely manner; moreover, emotion including fear, satisfaction, hope, and interest will simultaneously occur and interfere with the sorting out of such information. Indeed, human emotion affects health information retrieval, which will also directly affect one's perception and social cognition; moreover, it will also indirectly affect one's attitudes and behaviors in the use of the platform system (Myrick, 2017).

H_2: Platform system quality (SQ) will significantly (& positively) affect user's PB.

While the psychological mechanism underlying online health information retrieval is complex, platform SQ plays a key role in ensuring its acceptance and adoption. SQ combines multiple concepts, including but not limited to PU, perceived accessibility (PA), and others such as perceived ease-of-use (PEU) and subjective norms (SN), all of which can also significantly affect the users' adoption of online e-health services although some have argued that behavioral control, innovation, and trust may not significantly influence user adoption behavior (Bansal, Zahedi, & Gefen, 2010; Lin, Zhang, Song, & Omori, 2016). If users are to continue using online medical care, the creation, adoption and use of new high-tech products and services will be heavily dependent on its associated platform SQ.

H_3: Platform convenience will significantly (& positively) affect user's PB.

As new features are continuously adopted by online medical platforms, innovative factors have become important predictors of a user's continuous use. Convenience is defined as "time and effort saved by customers while purchasing and using a service (Berry, Seiders, & Grewal, 2002)". Convenience is an important determinant of customer behavior as a result of significant changes in customers' socio-economic profile, rise in dual income families, and a hypercompetitive marketplace (Seiders, Voss, Godfrey, & Grewal, 2007; Srivastava & Kaul, 2014). Hsu (2010) reports that an overall measure of convenience interacts with satisfaction in influencing consumer loyalty. Colwill, Aung, Kanitkar, and Holden (2008) note that all types of conveniences influence satisfaction.

Online medical care has changed the way in which public health information is transmitted. The anonymity of online health information provides convenience for patients to search for health problems.

H_4: Users' perceived reliability is expected to significantly (& positively) affect doctor reliability (DR).

Reliability is the degree for which an assessment of the service can provide stable and consistent results. Oort (2016) defines service reliability as the certainty of service aspects compared to the schedule such as travel time, including waiting, arrival time and seat availability as perceived by the user. Service variability is defined as the distribution of output values of the supply side of public transport, such as vehicle trip time, vehicle departure time and headways.

In the last decade, more attention has been paid to service reliability (SR). SR is one of the mainstay quality aspects of public health service. Improved SR increases the overall quality of public health, thereby ensuring quality and efficient services for patients while reducing the incidence of diseases. SR is an important quality characteristic in public health service. In this research, however, our focus will be on the online doctor reliability (DR).

H_5: Users' trust tendency will significantly (& positively) affect DR.

Quality servicing will signal service providers' ability and benevolence; in contrast, users cannot build trust in service providers if their services are unreliable with slow responses (Gao & Waechter, 2017). (Mallat, 2007) emphasizes that mobile network reliability is a common concern among the users who are worried that the network connection may fail in the middle of a payment transaction.

Trust is broadly defined as "the willingness of one party (trustor) to depend or rely on the actions of another party (trustee)" (Bisdikian et al., 2014). Trust and satisfaction can affect the patients' intention to consult online doctors, noting that such continuous online consultation intention does eventually affect the offline behavioral intentions. The fair perception of online doctors affects trust and satisfaction (Chang & Hsu, 2019). Today, an increasing number of patients are using the electronic appointment system to arrange for medical treatment programs. According to Kitsios, et al. (2019), PU and PA have positive effects on patients' satisfaction as well as the use of hospital e-reservation systems.

In countries with high economic development levels, the PA of users has a significant impact on PU; in countries with low economic development levels, innovation has a significant impact on users' use intention (Zhao, Li, & Zhang, 2019).

H_6: Users' PB will significantly (& positively) affect DR.

Altogether, the users' PB resulting from use of online platform may be dependent on the PU, satisfaction, and recognition - the three key factors affecting a user's continued use of online medical platforms (Alsohime et al., 2019; Rajković, Aleksić, Janković, Milenković, & Petković, 2018). Health guidance is positively related to a user's satisfaction (Leung & Chen, 2019a). PU, recognition, innovation, optimism, and age have become important predictors of lifestyle improvement (Balapour, Reychav, Sabherwal, & Azuri, 2019; Leung & Chen, 2019b). Users employ online medical platforms can promote changes in their healthy lifestyle behaviors (Leung & Chen, 2019a).

The influencing factors of neurologically disabled people accessing medical services online have also received research attention. PU and accessibility are significantly and positively correlated with patients' willingness to retrieve online health information. The negative interactions between PU and PA can predict the willingness to use online health information retrieval (H. Liang, Xue, & Chase, 2011). When users begin to rely on and trust the use of these online platforms, it is expected that the online doctor reliability (DR) will also be positively impacted.

H_7: Users' PB will significantly (& positively) affect intention to pay (ITP).

PB is positively related to the users' intention to use an online medical platform, whereas perceived cost is inversely related to the users' intention to use online medical care(Shawahna & Abdelhaq, 2020; Shim & Jo, 2020) .

Similarly, the cost of silence in traditional medical services is positively related to the expected benefit of online medical services, and habits of traditional medical services are negatively related to PB in online medical services (Sara Atanasova et al., 2018; X. Zhang, Guo, Wu, Lai, & Vogel, 2017b). As well, the cost of conversion is positively related to the perceived cost of online medical care; and the privacy protection benefit of traditional medical services is positively correlated with the perceived cost of online medical services (X. Zhang, Guo, Wu, Lai, & Vogel, 2017a).

With greater intent, the users' ITP will be augmented as well.

H_8: DR will significantly (& positively) affect ITP.

Given that medical resources are limited, the government hopes to use the online medical community to help patients obtain the necessary treatment. The role of reputation in e-commerce has been largely confirmed, and the reliability and reputation of the attending doctors and colleagues will have a significant impact on patients sharing their experience via the Internet.

Colleague reputation has a negative regulatory effect on the relationship between the reputation (and reliability) of the attending doctors and the sharing of treatment experience with patients (Hong Wu & Lu, 2016). Put simply, DR will be expected to generally affect patients' intention to use the online platform, which will in turn impact on their ITP.

H_9: The risk of misdiagnosis will positively regulate the relationship between user trust and DR.

Previous studies that tested unidirectional models inferred that trust enjoys a positive relationship with intent (Kim, Ferrin, & Rao, 2008). As time passes by, the rate of addressing health issues through online healthcare has increased, and users are increasingly recognizing that online health information can help solve health problems (Redston, de Botte, & Smith, 2018).

The integration of information and communication technology (ICT) into healthcare practices has reached a success milestone. The privacy protection of patients has attracted the attention of researchers. The use of reasonable security mechanisms to protect the privacy of patients plays a key role in the e-health system, realizing the fair use of e-health information (Gardiyawasam Pussewalage & Oleshchuk, 2016).

The communication between online medical and offline hospitals has a strong relationship and regulates the reputation, including trust and reliability.

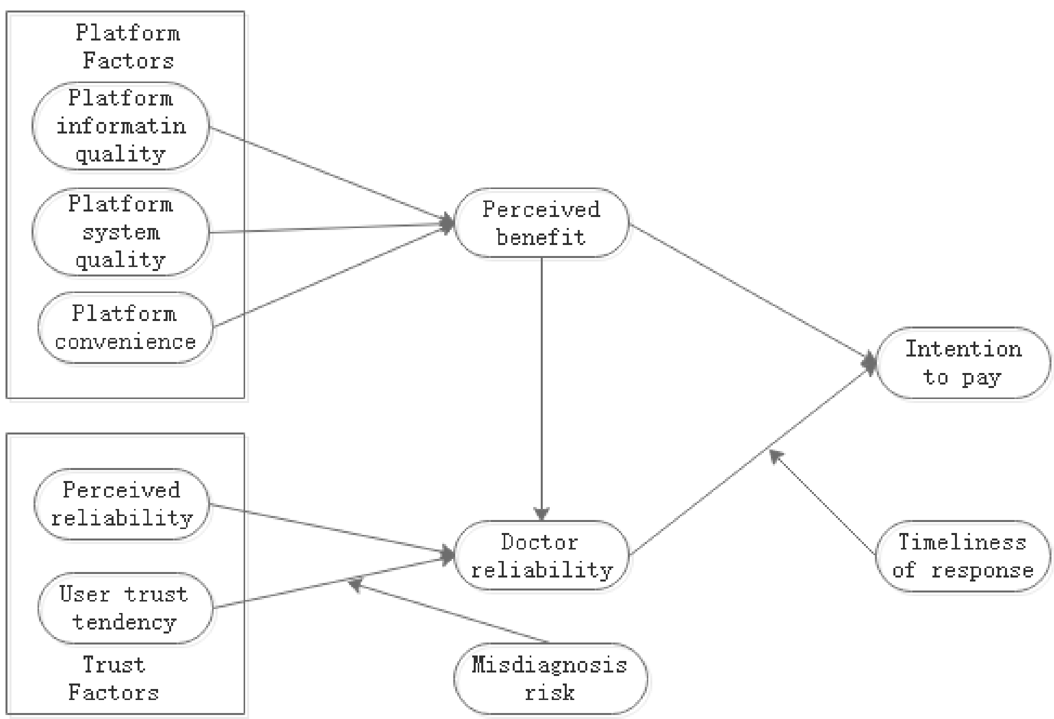
H_{10}: Responsive timeliness will positively regulate the relationship between DR and ITP.

Telephone consultations can easily replace online medical services, and doctors with high online-offline reputation can attract additional patients to use online medical services. Doctors with high online reputations can reduce the substitution effect of telephone consultation on online medical services (H. Wu & Lu, 2017).

The social media environment also allows patients to obtain health information. Service quality and responsive timeliness will also positively affect patient satisfaction. Service price and satisfaction have an inverted U-shaped relationship. At a low price level, service price will increase patients' satisfaction, and spreads between doctors' different services can significantly reduce patients' satisfaction (H. Wu & Lu, 2018).

Based on the aforementioned theoretical assumptions and rationalization, **Figure 1** depicts the research model applicable to our study.

Figure 1. Conceptual model of this study



4. RESEARCH METHODS

In this section, we present the data sampling and collection methods as well as the rationale underlying the data analytical procedures.

4.1 Questionnaire for Data Collection

In this study, data are gathered via a questionnaire instrument based on the theoretical constructs as provided in the research model depicted previously in **Figure 1**.

The questionnaire comprises two parts, one of which is the basic information to be gathered by the investigators, including eight (8) questions on demographical factors such as gender, age, and income. The second part is the measurement scale, including 15 measurement items such as ITP, quality of platform system, and quality of platform information.

The model variables are measured via the maturity scale based on the extant literature and scored by using a 7-point Likert-scale, with "7" representing the highest level of agreement and "1" the lowest. Prior to administering the formal questionnaire, 20 users who have used the online medical platform have been selected in order to pretest or pilot the questionnaire items. Questions with unclear meanings are identified, then these are either deleted or modified so as to ensure the validity of the contents.

Questionnaires are then distributed via Wenjuanxing. A total of 400 submitted responses to questionnaires have been collected. After a careful analysis of the questionnaires' response quality, 88 questionnaires containing missing or incomplete responses are removed. This resulted in a total of 312 validly responded questionnaires to be analyzed, with the effective recovery rate of 78%.

4.2 Data Samples

To obtain relevant and meaningful data for analysis, respondents to the questionnaire are largely chosen from among patients or would-be patients who have actually used an online medical platform.

Table 1 presents the basic information gathered from the administered survey instrument.

As shown, 54.49% of the study subjects is mainly concentrated in the population aged from 26–35; these individuals have generally been through a junior college education or have bachelor degrees, accounting for 88.46% of the total participating population. The occupation ratio of the research subjects, grouped from high to low is as follows: technicians & senior managers in enterprises (49.68%), institutional staff & civil servants (23.72%), students (13.14%), and teachers (7.69%).

Here, we investigate ways in which users interact via online medical care servicing. As tabulated, the highest proportion comprises those who are recommended to using online medical platforms via the website (64.1%), while a smaller portion is those who are recommended by friends (29.17%). Moreover, the majority income of the survey subjects is in the range of 5000–8000 Yuan, accounting for 67.63% of total population.

As for the users' acceptance of online medical expenses, about 50% of the respondents said that their accepted expense for online medical service platform is 10–50 Yuan each encounter, 17.63% respondents will accept expense of <10 Yuan, while 24.68% will accept a range of between 50–200 Yuan.

4.3 Reliability-Validity Analysis

For reliability-validity analysis, the aggregated data have been analyzed via a range of metrics, including, Composite reliability (CR), average variance extracted (AVE), factors loading, and reliability (Cronbach's α). **Table 2** shows the different measurement results obtained via Smart PLS3 software.

Reliability analysis is a test of the consistency of observations corresponding to the construct. Generally, when the CR and Cronbach's α values are >0.7, it can safely be assumed that the reliability is good. For this study, **Table 3** shows that all CR values are >0.8, and Cronbach's α >0.7, thereby indicating that there is good reliability of responses to the questionnaire, and the resulting scale demonstrates a good consistency.

Validity analysis refers to the degree to which the measurement item can accurately reflect the measured construct and is divided into structural and content validity. The items in the administered questionnaire have all been derived from the scale of the extant literature, with good content validity.

Table 1. Demographic statistical characteristics of the effective samples

Variable	*Category*	*Frequency*	*Percentage (%)*
Gender	Male	123	39.42
	Female	189	60.58
Age	18 and below	2	0.64
	19–25 years old	80	25.64
	26–35 years old	170	54.49
	36–45 years old	49	15.71
	>45 years old	11	3.53
Education	Junior middle school and below	0	0
	Senior middle school/technical secondary school/technical school	0	0
	Junior college/bachelor	276	88.46
	Master	36	11.54
	Doctor	0	0
Occupation	Institutional staff and civil servants	74	23.72
	Technicians and senior managers in enterprises	155	49.68
	Teachers	24	7.69
	Students	41	13.14
	Housewives	2	0.64
	Freelancers	9	2.88
	Others	7	2.24
Monthly income	£1000 yuan	18	5.77
	1001–2000 yuan	15	4.81
	2001–3000 yuan	11	3.53
	3001–5000 yuan	57	18.27
	5001–8000 yuan	109	34.94
	>8000 yuan	102	32.69
Pathways of understanding online medicine	Website recommendation	200	64.1
	Promotion on TV	17	5.45
	Recommendation from friends	91	29.17
	Others	4	1.28

Therefore, it is not surprising that the factor loading of all items in the questionnaire is >0.7, indicating that the scale has good polymerization validity.

The convergence validity of the model is good when the AVE of all variables is >0.5, and the validity of the model is good when the arithmetic square root of AVE of all factors is greater than the correlation coefficient among the factors.

For structural validity analysis, the study uses the AVE. As evidenced in **Tables 2** and **3**, the AVE of each variable is >0.5, and the arithmetic square root of each factor AVE is greater than the correlation coefficient among variables, thereby indicating that the questionnaire has good structural validity.

Table 2. Reliability analysis

Variable	Measured item	Factor load	AVE	CR	Cronbach' α
User trust tendency (UTT)	UTT1	0.842	0.653	0.882	0.822
	UTT2	0.791			
	UTT3	0.848			
	UTT4	0.747			
Intention to pay (ITP)	ITP1	0.880	0.758	0.904	0.841
	ITP2	0.882			
	ITP3	0.850			
Doctor reliability (DR)	DR1	0.706	0.581	0.874	0.819
	DR2	0.765			
	DR3	0.778			
	DR4	0.804			
	DR5	0.755			
Perceived reliability (PR)	PR1	0.853	0.723	0.887	0.808
	PR2	0.877			
	PR3	0.820			
Platform convenience (PC)	PC1	0.849	0.648	0.846	0.728
	PC2	0.762			
	PC3	0.801			
Platform information quality (PIQ)	PIQ1	0.762	0.613	0.826	0.701
	PIQ2	0.829			
	PIQ3	0.756			
Platform system quality (PSQ)	PSQ1	0.793	0.630	0.836	0.707
	PSQ2	0.789			
	PSQ3	0.799			
Perceived benefit (PB)	PB1	0.774	0.647	0.846	0.727
	PB2	0.836			
	PB3	0.802			
Timeliness of response (TR)	TR1	0.953	0.914	0.955	0.906
	TR2	0.959			
Misdiagnosis risk (MR)	MR1	0.844	0.753	0.902	0.837
	MR2	0.871			
	MR3	0.889			

5. STUDY RESULTS

As shown in the research model, the analysis of the various constructs vis-à-vis their relationships was conducted via Smart PLS 3.0 to assess the measurement items while simultaneously estimating the path of the structural model (Ringle et al., 2012).

Table 3. Validity analysis

	User trust tendency	Intention to pay	Doctor reliability	Perceived reliability	Platform Convenience	Platform information quality	Platform system quality	Perceived benefit
User trust tendency	0.808							
Intention to pay	0.434	0.871						
Doctor reliability	0.573	0.633	0.762					
Perceived reliability	0.452	0.672	0.735	0.850				
Platform convenience	0.415	0.571	0.602	0.574	0.805			
Platform information quality	0.413	0.603	0.627	0.755	0.575	0.783		
Platform system quality	0.350	0.432	0.525	0.566	0.433	0.615	0.794	
Perceived benefit	0.447	0.614	0.655	0.683	0.723	0.650	0.518	0.804

While other SEM tools exist, the choice to use PLS was driven by several factors:

- The calculation results of PLS are more reliable and stable than those of other methods. The bootstrapping procedure was applied to achieve a stable set of standard error estimates (Hoque, Albar, & Alam, 2019).
- Wold (1981) specifically advises that the PLS is not suited for confirmatory testing; rather, it should be used for prediction and the exploration of plausible causality. PLS can set the external relationship type in the structural equation flexibly according to the actual situation when constructing the model, that is, it supports the constitutive and reflective models.
- The main purpose of PLS is to construct regression models between multiple dependent and independent variables. PLS does not make the assumption of multivariate normality that the SEM techniques such as LISEREL and AMOS do, and being a nonparametric procedure, the problem of multicollinearity is not perceived to be an issue (Ringle et al., 2012).

Moreover, the requirement for using PLS on the current sample size is lower than those of other SEM techniques (Chin, 1998; Westland, 2007) as PLS has no special requirement for data distribution and can achieve modeling prediction, comprehensive simplification of multivariable systems, and correlation analysis between two sets of variables.

5.1 Path Coefficient and Hypothesis Testing

The path coefficient indicates the strength of the relationship between the independent and dependent variables. Here, results of the path coefficient analysis are shown in **Figure 2** and **Table 4**. Apparently, the findings indicate all proposed hypotheses to be supported.

R^2 is the variance variability as explained by the dependent variable. In this study, bootstrap repeated sampling method is used to select 1000 samples to calculate the t-value of the significance test. The interpretation degrees of PB, DR, and ITP are 0.615, 0.640, and 0.504 respectively, thereby indicating that the model has a good interpretation effect.

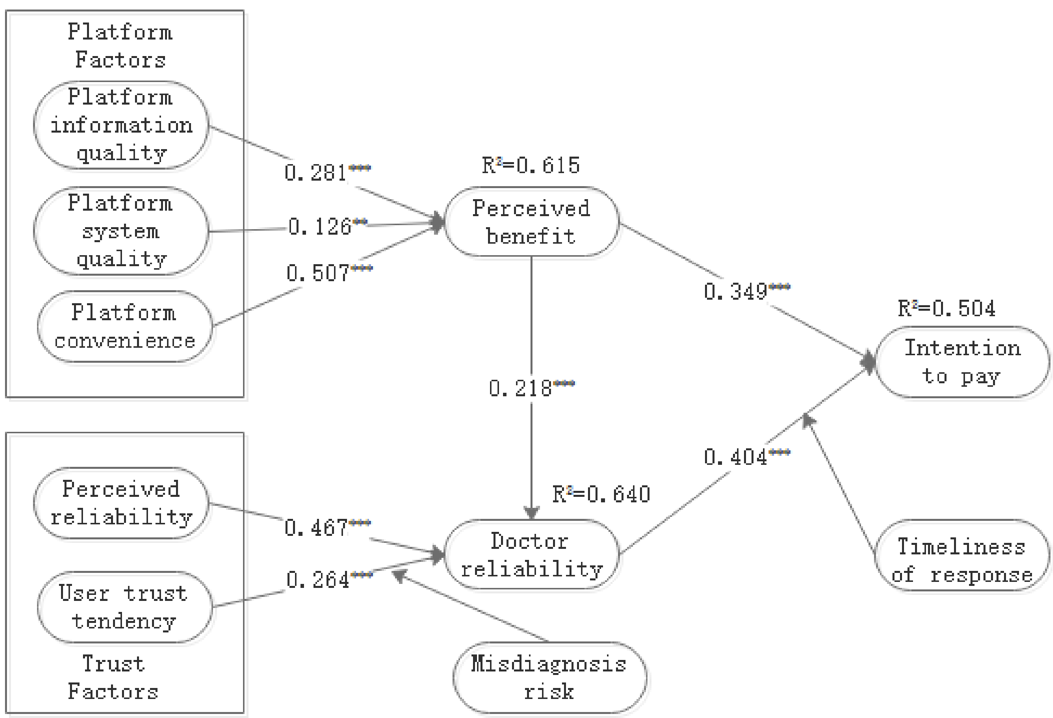
5.2 Regulatory Effect Tests

To test the regulatory effects of misdiagnosis risk (MR) and timeliness of response, the independent and regulatory variables to construct the product of MR, user intention, DR, and ITP have been centralized and multilayer regression analysis was conducted.

Table 4. Results of hypothesis tests

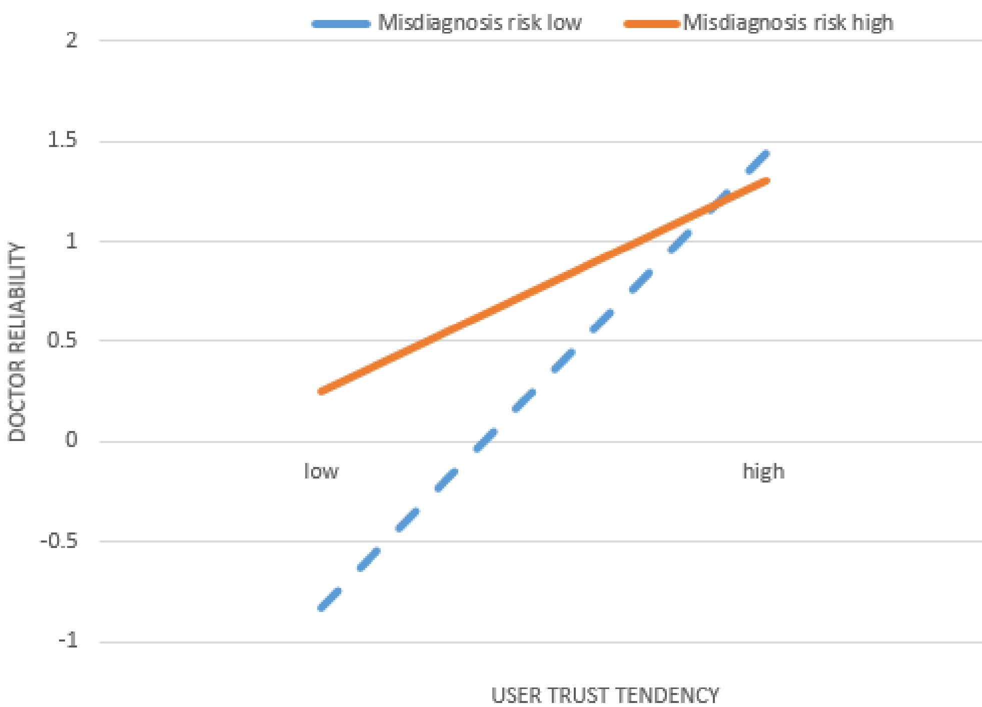
Hypothesis	Path	Supported or not
H1	Platform information quality → perceived benefit	Yes
H2	Platform system quality → perceived benefit	Yes
H3	Platform convenience → perceived benefit	Yes
H4	Perceived reliability → doctor reliability	Yes
H5	User trust tendency → doctor reliability	Yes
H6	Perceived benefit → doctor reliability	Yes
H7	Perceived benefit → intention to pay	Yes
H8	Doctor reliability → intention to pay	Yes
H9	Misdiagnosis risk + user trust tendency → doctor reliability	Yes
H10	Timeliness of response + doctor reliability → intention to pay	Yes

Figure 2. Model path coefficient and significance level



The MR is divided into high v. low conditions, which can facilitate the clear display of the role of regulatory variables. SPSS is used to draw the effect degree of user trust on the DR when the MR is high v. low, with R^2=0.243 and 0.236 after adjustment (p=0.003, F=9.122, and sum of squares of class III is 1.743). **Figure 3** shows the adjustment effect.

Figure 3. Regulatory effect of MR on the relationship between UTT and DR



As shown, when the MR is high, the influence of user trust tendency on the DR is diminished. Based on the results, the MR has a significant regulatory effect on the relationship between user trust and DR.

To clearly reflect the regulatory effect of response timeliness of the platform, we first calculate the average number of the response timeliness and standard deviation, taking the positive and negative standard deviations of the average as the two levels of response timeliness, with R^2=0.278 and 0.271 after adjustment (p=0.028, F=4.896, and sum of the squares of class III = 0.886). Hence, results show that the corresponding timeliness of the platform also has a significant regulatory effect on the relationship between DR and ITP.

Figure 4 shows the regulatory effect. When the response timeliness of the platform is high, the influence of DR on the ITP is weakened.

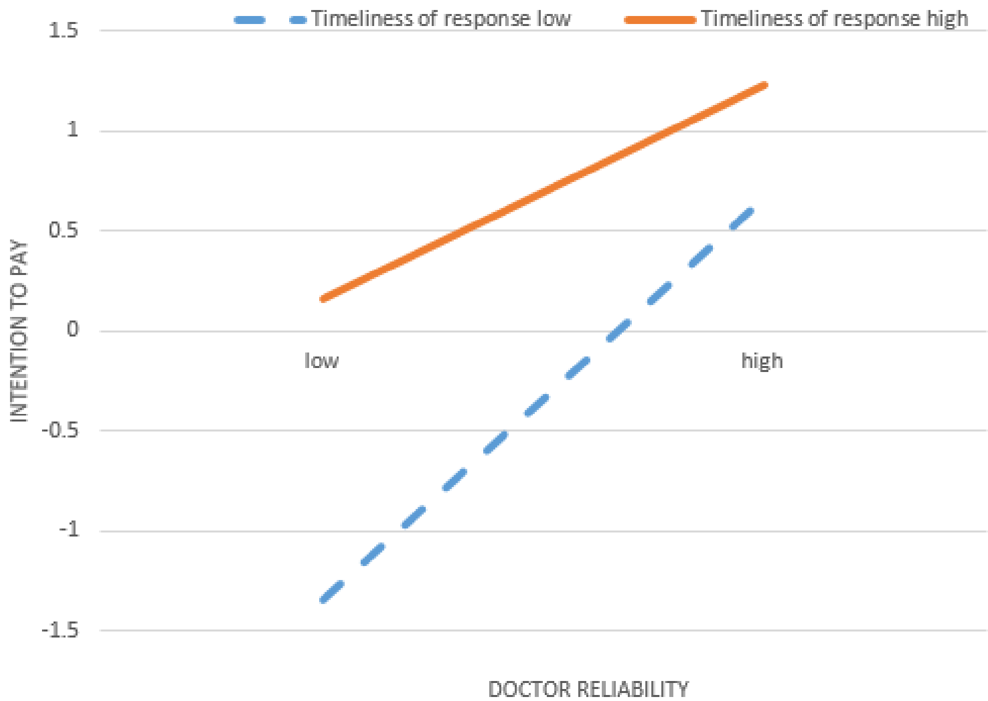
6. CONCLUSION

This study explores how platform performance and trust features affect individuals' ITP for online medical service. Here, prior to highlighting the study limitations and offering insights into future related works, we will first discuss key findings and their implications.

6.1 Discussion of Key Results

In line with the prior study results on online medical service of (Alsohime et al., 2019), IQ, SQ, as well as convenience of the platform have been found to significantly affect the users' PB. Importantly, users' PB are greatly influenced by online medical platform; hence, one should focus on system design, website structure optimization, the navigation design of the platform, and the effective

Figure 4. Regulatory effects of response timeliness on the relationship between DR and ITP



management of online medical platform information when developing online medical platforms. This will assist users to quickly access and understand information, save them time to browse and search for health information, increase their PB and improve their satisfaction with using the online platform. As well, the establishment of a good online medical image would boost one's trust in the online medical platform.

Another significant finding is that users' perceived reliability of the platform and their trust tendency can positively affect DR. This finding supports the arguments in prior studies that trust is an antecedent of DR (Chang, Hsu, Wang, & Chang, 2019; Kostagiolas, Korfiatis, Kourouthanasis, & Alexias, 2014). Perceived trust has a significant impact on one's willingness to use the platform. Indeed, online medical platforms should enhance the reliability and authenticity of medical health information to avoid the potential for misinformation. Meanwhile, the supervision of language norms of online medical platforms should be strengthened to prevent the spread of offensive information. Improving the relevant information of online doctors, such as name, specialty, professional title, and more will make it possible for users to know as much about the attending doctors as possible, which is conducive to reducing users' perceived risks.

Significantly, users' PB can positively affect their ITP and DR, while DR will in turn positively affect the users' ITP. These findings are partially consistent with results of (Chen, Yang, Zhang, & Yang, 2018). After repeatedly using the online medical services, users would gradually improve their PB and increase their trust in online doctors, thus positively affecting their willingness to pay.

As well, the study results show that MR positively regulates the relationship between the users' trust tendency and DR. The timeliness of the response of the platform also positively moderates the relationship between DR and users' ITP. This finding concurs with the results of similar research in the domain of health literacy (Qiao, Geater, Chongsuvivatwong, Fan, & Guo, 2017). When users seek medical services on the medical health platform, they hope that the online medical platform can provide timely and effective feedback. Moreover, they also hope that the online medical platform can propose personalized solutions vis-à-vis the users' differentiated needs.

Finally, in order to allow users to feel at home and want to be engaged, the online medical platform should provide timely feedback about the progress of the services being provided to the users, optimize the service processes, enhance the humanized characteristics of the online platform experience, and pay attention to the emotional communication between users and the healthcare professionals

6.2 Implications

Increasing number of multi-provider hospitals are now venturing into online platforms to provide distance or remote outpatient services. While extensive attention has been given to key factors affecting the development of such platforms, it is the support of external institutional forces and senior management that will strongly influence the eventual use and sustainability of these platforms.

Clearly, the beliefs of top managers will be influenced positively by simulated and forced stresses. As simulated stress v. other stresses will have a greater impact on the beliefs of top managers, it can be employed to drive the development of online medical platforms. The relationship between institutional power and e-health use will be mediated by the support of top managers (Hsia, Chiang, Wu, Teng, & Rubin, 2019). The compatibility, synergy, and integration capabilities of online medical platforms can effectively improve the performance of hospitals. Enhancing the compatibility of these platforms will allow the promotion of the synergistic effect of e-health, which can improve the performance of the healthcare organizations. Moreover, medical institutions can develop the compatibility and collaboration capabilities required for successful online medical platform servicing. The IT assets and organizational resources must be integrated to adapt to environmental changes so as to improve hospital benefits (J.-H. Wu, Kao, & Sambamurthy, 2016).

Social identity will also have a positive impact on the reliability of health information(Evans, Williams, Onnela, & Subramanian, 2018) . Just as with the general public, a trusted social verification can impact positively on the reliability of health information offered in the system; in fact, the perceived reliability of the health information correlates directly with the strength of its verification. Faced with information overload, social verification is key for users to trust the information. Hence, online medical platforms that want to improve information reliability should provide social verification mechanisms, such as rating systems. Users sharing experiences and providing information need to collect social verification information such as links to medical experts as trusted sources for them to be able to rely increasingly on the system (Jucks & Thon, 2017).

Motivation to improve the users' ITP for online medical service platforms is driven by studying comprehensively the factors of online medical service platform performance and patients' trust. The online medical service platform should improve its service quality, rationality and scientific design. The speed of information feedback and response time, as well as security and reliability of the platform information also play key roles for users to become engaged. A stable, convenient, and secure online medical service platform can enhance the users' sense of pleasure and reduce the perceived privacy risk involved in personalized services.

Moreover, users' trust in online doctors and websites needs to be assured when using online medical service platform. For example, providing value-added medical information to users via the platform allows users to obtain sufficient medical resources; stimulate users' gratitude, emotions, and dependence; and promote their trust when interacting with the doctors online as well as the websites.

Finally, the online platform can leverage partnering hospitals, departments, and doctors to recruit additional doctors to adopt the technology, promote the conversion between online and offline services, and improve the communication of core information, such as medical records, prescriptions, and test results in a timely and convenient fashion. The Big Data analytics may also be used to offer a better grasp of the users' movement rules, life habits, and eating habits to improve the accuracy of online medical services and standardize the management of online medical service platforms.

6.3 Limitations and Future Research

Despite its contributions, this research has limitations that may be better addressed in future studies. As we know, users' personal health information literacy is the basis for medical information retrieval and it has an important impact on the ITP. However, users' personal health information literacy is yet to be included in the research model, and a suitable scale is needed to measure this item.

Moreover, while this paper explores the impact of an online medical service platform and trust factors on users' ITP, many other factorial and boundary conditions remain to be considered, for example, personality characteristics and cultural backgrounds. In fact, the online reputation of doctors could have been included as supplementary research variables if more funds have been available to explore its influence on the continuous use of online medical treatment by users. Meanwhile, the interaction between online and offline efforts and reputation can be further studied, compared and/or contrasted.

Finally, even though the scale measurement of the current study shows good reliability and validity, the questionnaire data can also be vastly expanded via multiple sources to encompass additional objectives and achieve a broader investigation. In the future, with new features to be developed for improved online medicine platforms, questionnaires can be more widely distributed to collect data (for example: perceived service attitudes, privacy protection)that can be matched and integrated to encompass these additional objectives, driving more research. Based on the perspective of multi-party interaction, the online medical service delivery process and service management process will be studied to promote the continuous communication between doctors and patients, in turn, to achieve the sustainable development of online medical service.

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APPENDIX A. QUESTIONNAIRE: MEASURED ITEMS

PIQ
PIQ1: The online medical consultation platform provides perfect doctor introduction and health science popularisation information.
PIQ2: The health information provided by the online medical consultation platform is easy to understand.
PIQ3: The consultation information provided by online medical treatment meets my needs.
PSQ
PSQ1: The user interface for online medical treatment is well designed.
PSQ2: Online medical treatment can quickly load all graphic, audio and video information.
PSQ3: I can easily find the navigation of the online medical website.
PC
PC1: I can conduct health consultation without leaving home by using online medical treatment.
PC2: I can conduct health consultation anytime, anywhere by using online medical treatment.
PC3: I can save time and energy to go to the hospital by using online medical treatment.
PR
PR1: Overall, the quality of online medical and health services is relatively high.
PR2: The use of online medical and health services will provide me with emotional consolation.
PR3: The use of online medical and health services is reliable.
UTT
UTT1: I generally trust others.
UTT2: I generally trust human nature.
UTT3: I think people are usually trustworthy.
UTT4: I usually trust others, unless there is a reason for me not to do so.
PBs
PB1: The use of online medical and health services is convenient.
PB2: The use of online medical and health services will help to improve my health level.
PB3: The use of online medical and health services can save time
DR
DR1: The doctor will put my needs first
DR2: I will follow the doctor's advice
DR3: Generally, what the doctor told me was credible
DR4: I believe the doctor's judgment on my condition
DR5: I think the doctor will consider all the conditions during the diagnosis and treatment.
MR
MR1: The advice and suggestions provided by the doctors in online medical treatment may not be applicable, and it may even harm the health.
MR2: The misdiagnosis rate of online health consultation may be higher due to the lack of face-to-face diagnosis.
MR3: Registering in and using online health consultation are risky for doctors, considering the expected service level of doctors in online medical treatment.
TR
TR1: It will take a long time to get a reply from the doctor after requesting consultation in an online medical treatment platform.
TR2: The doctors in online medical treatment can timely answer my questions online.
ITP
ITP1: I definitely want to pay for an online health consultation.
ITP2: I will absolutely consider paying for an online health consultation.

ITP3: I will very likely pay for online health consultations soon.

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