Local Administration Journal 17(2) • April - June 2024 • 129-154
Received: April 16, 2024 • Revised: May 15, 2024 • Accepted: June 6, 2024
RESEARCH ARTICLE

Factors Impacting People Performance Expectancy and Behavioral Intention with the Internet Medical Service in Chengdu, China

Yixi Yang
Vincent Mary School of Science and Technology, Assumption University, Thailand; Chengdu University, China; Chengdu Medical College, China

Paitoon Porntrakoon
Vincent Mary School of Science and Technology, Assumption University, Thailand

Jian Li
Perclinical Medicine, Chengdu University, China

Abstract
This research examined patients' receptiveness to utilizing online medical services, explored the factors impacting their performance expectancy and behavioral intention, and offered actionable recommendations to enhance patient adoption and utilization of online medical services. The study was based on the unified theory of acceptance and use of technology and also drew upon the health belief model and social cognitive theory to elucidate the components. The cross-sectional survey included the participation of a total of 494 valid outpatients from the first affiliated hospital founded by the Chengdu Medical College of China through the use of convenience sampling and purposive or judgmental sampling. With Cronbach's alpha and composite reliability greater than 0.7 and the average variance extracted greater than 0.5, all of the constructs demonstrated a satisfactory level of reliability and validity. Each and every one of the research hypotheses was validated. Both social influence and facilitation conditions were shown to have a considerable impact on performance expectancy, as evidenced by the statistically significant β values of 0.436 and 0.344 ($p<0.001$), respectively. The behavioral intention was substantially affected by resistance to change, effort expectancy, perceived security, performance expectancy, and perceived disease threat, as indicated by the β values of -0.196, 0.367, 0.308, 0.223, and 0.307, respectively, with p-values less than 0.001. Effort expectancy significantly predicted the behavioral intention to promote the adoption of Internet medical services. Therefore, the promotion of Internet medical services should focus on individuals who are well-educated and have basic IT skills. Regular training sessions should be provided to broaden the intended user group.

Keywords
internet medical service, performance expectancy, behavioral intention, UTAUT, SEM

CORRESPONDING AUTHOR
JIan Li, Perclinical Medicine, Chengdu University.
No. 2025 Chengluo Ave. Longquanyi District, Chengdu, 610106, China. Email: liJian01@cdu.edu.cn

Introduction

The embryonic form of Internet healthcare could be traced back to the emergence of telephone diagnosis and treatment. In 1879, the Lancet publication made reference to the potential application of the telephone as a means to alleviate the demands associated with face-to-face medical consultations (Dash, 2020). During the early 2000s, the global medical and health sector faced the challenge of increasing multi-level and personalized medical and health needs from the public as the aging population intensified and the prevalence of chronic diseases remained high (Fan et al., 2022). On the other hand, it also faced practical difficulties, such as uneven allocation of medical resources, overcrowding of large hospitals, and serious problems for patients seeking medical treatment (Lai et al., 2021). In this situation, the idea of Internet medical services was created, which had been instrumental in enhancing the availability of high-quality medical resources, thus contributing to the equitable distribution of medical resources and the restructuring of the healthcare system.

The so-called Internet medical service referred to the new application of the Internet in the medical industry, including various forms of health butler services such as health education, medical information query, electronic health records, disease risk assessment, online disease consultation, electronic prescribing, remote consultation, remote treatment and rehabilitation based on the Internet as a carrier and technical means (Rana et al., 2021; Srivastava et al., 2022).

The digital economy in China has witnessed enormous expansion since the early 2000s, leading to a significant uptake of digital services within the country (Ito, 2019). Within this specific framework, the Chinese government had adopted the national policy of Internet Plus Healthcare to facilitate the utilization of the Internet in the process of reforming, modernizing, and enhancing the healthcare sector (Li et al., 2020). There was an investigation about web-based medical consultation in China by Li et. al. (2019). As of September 23, 2017, a total of 88308 doctors, which represented 5.325% of the entire medical population in China, engaged in web-based consultations only during their leisure hours on an Internet medical platform. As of the beginning of 2019, the top 14 Chinese medical and health unicorns were involved in online hospital-related businesses (Deloitte, 2021). Based on the correspondence issued by the NHC (2021), a cumulative count of more than 1,700 online hospitals had been established nationwide; yet, a majority of these facilities were predominantly concentrated in the eastern region of China.

However, the development of Internet diagnosis and treatment businesses not only requires the active participation of physical medical institutions and Internet enterprises, but also requires patients to transform traditional diagnosis and treatment models and form online medical habits (Xu et al., 2021). Therefore, the attitude of patients largely determines the sustainable development of the Internet medical service, which will also become a focus of attention for some medical institutions that hold a wait-and-see attitude toward the Internet medical service.

Objectives

Published studies of the behavioral intentions of the Internet medical service in China are still scarce, and the number of studies is not in line with the rapid development in the area of Internet technology (IT). Chengdu City in particular, with the largest population in southwest China and far from coastal cities, has a unique geographic location, advanced economy, and top level Internet medical service. Thus, a research question that needed to be answered was: What factors impact the behavioral intention to use the Internet medical service directly and indirectly in this advantaged Chinese provincial capital city? The current research aimed to examine patients' receptiveness to utilizing online medical services and explore the factors impacting their performance expectancy and behavioral intention.

Theory and Prior Studies

This study was based on a number of theories. The unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) was the key theory. In this study, additional theories were also used to help understand behavioral intention and user behavior in the areas of online medicine, Internet "plus," Internet shopping, Internet education, and other spheres of online activity. These theories include the health belief model (HBM) (Champion & Skinner, 2008) and social cognitive theory (SCT) (Compeau & Higgins, 1995).

UTAUT was primarily employed to conduct research on the variables that influence how consumers utilize and accept new products and technology. The UTAUT framework encompasses four primary variables: performance expectancy, effort expectancy, social influence, and facilitating conditions.

The HBM encompasses various fundamental concepts that serve as predictors for an individual's inclination to engage in actions aimed at preventing, screening for, or managing sickness. These concepts encompass susceptibility, seriousness, benefits, and barriers associated with specific behaviors, cues to action and, more recently, self-efficacy (Rosenstock, 1974; Bandura & Wessels, 1994).

Bandura (1977) produced a seminal article on self-efficacy, which became a milestone in the field of SCT. The field of study recognized the significant influence of social modeling on human motivation, cognition, and behavior. SCT had emerged as a foundational framework in various fields of psychology, including clinical, educational, social, developmental, health, and personality psychology (Ratten & Ratten, 2007).

Conceptual Framework

The framework for this research study is based on three theoretical frameworks. Zhang et. al. (2019) developed a comprehensive theoretical framework to determine the elements that impact patient intent to use diabetes management applications in the current context. The second theoretical framework was developed and implemented by Hoque and Sorwar (2017). The aim of their study was to address the aforementioned gaps by examining the adoption and acceptance challenges of m-health (mobile health) from the perspective of older individuals in a resource-constrained setting, such as Bangladesh. In addition, the third theoretical framework (Shahbaz et al., 2019) initially used the technology acceptance model to shed light on the adoption of big data analytics (BDA) by healthcare companies. That study examined the factors influencing user adoption of BDA, while acknowledging the potential oversight of system implementation considerations.

For the purpose of this study, the four elemental variables from the first theoretical framework (based on the UTAUT model) were chosen, including social influence, facilitation conditions, performance expectancy, and behavioral intention, as well as the variable of perceived disease threat from HBM theory. The second theoretical framework offered two variables: effort expectancy and resistance to change. Perceived security was adapted from the third theoretical framework. Figure 1 depicts the resulting research framework.

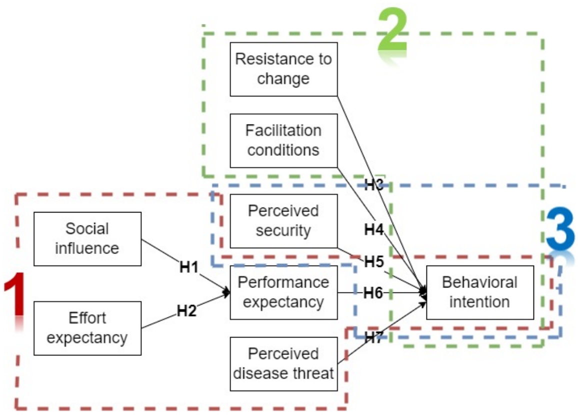

Figure 1. Research Framework

Also, if a model included the significant performance expectancy and effort expectancy constructs, then the facilitation conditions variable was no longer useful for forecasting a user's intentions with regard to the adoption and acceptance of technology (Venkatesh et al., 2003). Furthermore, as stated in the first theoretical framework, the variables of social influence, effort expectancy, and facilitation condition were identified as having indirect effects on behavioral intention. It was seen that social influence exerted the most notable indirect impact. Hence, the present study identified social influence and facilitation as factors that should indirectly impact behavioral intention, perhaps mediated by performance expectancy.

Alongside the foundational UTAUT model, this study was constructed to explain the factors impacting performance expectancy and behavioral intention with the Internet medical service in Chengdu, China.

Hypothesis

Social Influence

The component affecting how the service was actually used was social influence. For technology to succeed, the social influence factor is essential (Martins et al., 2014). According to Kijsanayotin et. al. (2009), social influence is the extent to which a person believed that significant others thought they should use health IT. The construct includes the idea that one's behavior is influenced by how they thought other people would perceive them as a result of using health IT. Cialdini and Goldstein (2004) discussed social influence in terms of the value of having correct views of reality and responding appropriately, as well as the relevance of building social connections and upholding a positive self-concept. People generally didn't like being in the dark, so they interacted with social networks to get advice and information (including normative social influence) before making a decision to use health IT (Burkhardt & Brass, 1990). Kristianto (2021) demonstrated that social influence had a favorable and considerable impact on how the Halodoc application (telehealth mobile) was used. Hence, the researcher proposes the following hypothesis:

H1: Social Influence (SI) has a significant impact on Performance Expectancy (PE).

Facilitation Conditions

Consumer awareness of existing technology support was defined as facilitating conditions (Salgado et al., 2020). Baumeister et. al. (2015) indicated that the facilitating conditions were technical infrastructure and technical support using Internet-based interventions. Different types of infrastructure were required, depending on the technology being used. For instance, applications in health support facilities that were essential include a strong Internet connection, a smartphone that worked well, and user expertise with the technology (Utomo et al., 2021). Facilitating conditions might be more crucial to electronic-based health (e-health) than other IT because it is typically utilized to respond to a unique medical issue (Wilson & Lankton, 2009). The main findings of Sobti (2019) suggest that facilitating conditions had a positive and considerable influence on the uptake of mobile services in India. Hence, the researcher proposes the following hypothesis:

H2: Facilitation Conditions (FC) have a significant impact on Performance Expectancy (PE).

Resistance to Change

Any dissident behavior that slows down, opposes, or obstructs a change management endeavor is referred to as resistance to change (Lines et al., 2015). Sometimes, as the word was most commonly used, “resistance” usually refers to “negative” actions and non-action, ill will, resentment, and a defensive or confrontational disposition (Starr, 2011). Thomson (2008) referred to the urge to reform, shift, criticize, or ignore change intentions as the driving force behind resistance to change. Bhattacherjee’s (2007) empirical investigation found that resistance to change was a major obstacle to the widespread adoption of information technology in the healthcare industry. Hence, the researcher proposes the following hypothesis:

H3: Resistance to Change (RC) has a significant impact on Behavioral Intention (BI).

Effort Expectancy

Effort expectancy refers to how simple it is (or not) to use an information system (Venkatesh et al., 2003). The foundation of effort expectancy is the notion that there are connections between the effort made at work, the results attained as a result of that effort, and the rewards obtained as a result of the effort (Ghalandari, 2012). In the medical arena, the likelihood that consumers accept an e-health technology increases with how simple it is for them to understand and utilize (Alpay et al., 2010). The degree of convenience connected with the remote access and use of the entire m-health system is how Dwivedi et. al. (2016) defined this notion, using a generic perspective of m-health. This notion is not unique. Hsieh (2016) discovered that effort expectancy has a direct and beneficial impact on a patient’s intention to use the ‘health cloud.’ Hence, the researcher proposes the following hypothesis:

H4: Effort Expectancy (EE) has a significant impact on Behavioral Intention (BI).

Perceived Security

People’s perceptions of the security and dependability of the Internet of things (IoT) are referred to as perceived security (Zhang et al., 2014). Based on a few indicators, people evaluated an organization’s degree of data protection. Peikari et. al. (2018) refer to this phenomenon as perceived security. In the context of Johnson et. al. (2019) define ‘perceived security’ as the belief that the vendor would take the necessary steps to ensure that technology usage was risk-free. Perceived security, according to Khan et. al. (2021), is a predictor of trust. A user’s level of confidence in technology depends on how secure they feel. A model for identifying the elements impacting an older user's perceptions of home telehealth services was developed and empirically evaluated by Cimperman et. al. (2016), who found that behavioral intention was directly impacted by perceived security. Hence, the researcher proposes the following hypothesis:

H5: Perceived Security (PS) has a significant impact on Behavioral Intention (BI).

Performance Expectancy

Ghalandari (2012) defined the degree to which a person expected that using the system might result in improved performance at work (i.e., 'performance expectancy'). Performance expectancy, as defined by Brown et. al. (2010), is the degree to which employing a technology benefits customers, and results in reliable performance enhancement. According to Sarfaraz (2017), performance expectancy refers to what users anticipated from the performance of accepted technology. A person's awareness of the benefits of utilizing a technical innovation that produces superior results is also known as performance expectancy (Zhou, 2008). Chong (2013) found that the most powerful predictor of behavioral intention to utilize mobile apps is performance expectancy. Hence, the researcher proposes the following hypothesis:

H6: Performance Expectancy (PE) has a significant impact on Behavioral Intention (BI).

Perceived Disease Threat

The importance of the perceived disease threat is typically highlighted, with less emphasis on the objective perception of the hazard than on the subjective experience of it (Tomaka et al., 1993). Rosenstock (1974) observed that perceived disease threat is frequently cited as a key determinant of health-related actions. The perceived disease threat is referred to as people dealing with uncertainty and unpredictability relating to disease threats, and generating behaviors relating to threat reduction strategies (Kim, 2020). According to Campbell et. al. (2020), the perceived disease threat had a negative impact on a consumer's ontological security, leading to behavioral (e.g., greater excessive consumption) as well as psychological (e.g., fear, anxiety) reactions. Hence, the researcher proposes the following hypothesis:

H7: Perceived Disease Threat (PDT) has a significant impact on Behavioral Intention (BI).

Behavioral Intention

According to Warshaw and Davis (1985), behavioral intention refers to a conscious decision to engage in or refrain from a particular behavior. Fishbein and Ajzen (1975) defined behavioral intention as an individual's intention to engage in a given behavior, and would be the best single predictor of that behavior. A person's feelings about engaging in the target activity (e.g., favorable or unfavorable) are referred to as behavioral intention (Shen et al., 2017). Saha and Nath (2017) asserted that behavioral intent could be referred to as anticipated future conduct and desired behavior. According to Spears and Singh (2004), behavioral intention refers to a person's propensity to act in accordance with his or her sentiments, knowledge, or assessments of prior experience.

Methods

In this study, the target population met the following requirements: Chengdu residents who had personal experience with Internet medical services for more than six months; Outpatient of the First Affiliate Hospital of Chengdu Medical College. This hospital was chosen because it is one of several tertiary, Grade A, comprehensive hospitals in Chengdu, with a large number of outpatients from all areas of Chengdu City. In addition, due to practical criteria such as geographical proximity, availability at a given time, and willingness to participate, the sample participants from this hospital were easily accessible. Consequently, the researcher was able to select the intended study population through the use of convenience sampling and purposive or judgmental sampling.

Purposive (judgment) sampling involves the intentional selection of participants based on specific inclusion criteria (Etikan et al., 2016). For the initial phase, purposive sampling was employed to choose outpatients of four departments from the First Affiliate Hospital of Chengdu Medical College. These four departments have a complete Internet medical service platform, and the majority of their outpatients have a chronic condition. Thus, the outpatients had a good possibility of being referred to the Internet medical service. Meanwhile, the second phase of the research utilized the stratified sampling method to establish distinct strata. The survey instrument was distributed to four departments as indicated in Table 1. Daniel Soper's calculator (Soper, 2006) determined that the minimum sample size required to detect an effect was 444. The researcher selected a sample size of 500 based on prior studies. Therefore, the sample size for each of the four departmental branches was equivalent to a combined total sample size of 500 (Malterud et al., 2016).

Table 1. Number of Questionnaires Distributed to Each Department

Four Main Departments	Outpatient Population (per year)	Proportional Sample Size
Department of Gastroenterology	62, 190	135
Department of Neurology	34, 578	75
Department of Cardiovascular Medicine	81, 002	175
Department of Endocrine Metabolism	53, 107	115
Total	230, 877	500

Source: The data comes from official website of the first affiliated hospital of Chengdu medical college https://www.cyfyy.cn/.

In the final phase, the researcher used convenience sampling of participants based on factors such as their geographical proximity, accessibility in a specific timeframe, and willingness to participate in the study (Simkus, 2022). The study employed a questionnaire, which was disseminated through various social media applications (e.g., WeChat, QQ, Wenjuanxin). The online survey was conducted during October 2023 to January 2024. In all, 494 questionnaires met all requirements and were qualified to provide the data for the analysis.

The analysis was carried out in multiple stages. The initial portion presents a descriptive analysis of the demographic data of the sample. The second segment analyzed the data set for skewness and kurtosis. The third portion was confirmatory factor analysis (CFA) to assess the validity and reliability of the measurement model. The fourth portion produced the structural equation modeling (SEM) for the structural model's fitness.

Findings

Demographic Information

Table 2 shows that, out of the 494 participants, 49.4% were male and 50.6% were female. The majority of participants had attained a bachelor's degree or higher, accounting for 86.0% of the total. Out of all participants, just one individual lacked literacy skills, while three individuals had only attained elementary school education. Furthermore, 39.1% of the participants fell within the age range of 18 to 35 years. Among these individuals, 36.8%, 10.7%, and 13.4% were age 35 to 50, 50 to 65, and above 65 years, respectively. The majority had a monthly salary above 4,000 RMB, accounting for 65.6% of the population. One-fifth (19.8%) of the sample had monthly income below 2,000 RMB, while 14.6% earned between 2,000 and 4,000 RMB. The monthly minimum salary standard in Chengdu City is 2,100 RMB. The participants consisted of individuals from various occupations, such as student, medical professional, government employee, state-owned enterprise worker, private enterprise employee, self-employed, freelancer, and retiree. These groups accounted for 22.9%, 17.8%, 16.6%, 7.3%, 13.0%, 6.3%, and 16.2%, respectively. Nevertheless, the e-health usage behavior of all these individuals was not particularly high, as 85.8% of participants utilized the Internet medical service only 1 to 2 times a month. Out of the total of 494 participants, only 38 individuals utilized the Internet medical service between 3 and 6 times per month. Notably, out of the 494 participants, 32 utilized the Internet medical service more than 7 times a month. This suggests that these individuals had already developed a habit of using the service, and their frequency of usage remains consistently high.

Table 2. Demographic Information

Demographic and General Data (N=494)		Frequency	Percentage
Gender	Male	244	49.4%
	Female	250	50.6%
Highest degree	Illiterate	1	0.2%
	Elementary school	3	0.6%
	Junior high school	19	3.9%
	Senior high school	46	9.3%
	Bachelor degree	304	61.5%
	Master degree or above	121	24.5%
Age	18-35 years old	193	39.1%
	35-50 years old	182	36.8%
	50-65 years old	53	10.7%
	More than 65 years old	66	13.4%
Salary per month	Below 2000 RMB	98	19.8%
	2,000-4,000 RMB	72	14.6%
	4,000-8,000 RMB	174	35.2%
	Above 8,000 RMB	150	30.4%
Occupation	Student	113	22.9%
	Medical staff	88	17.8%
	Employee of a government agency/institution	82	16.6%
	Employee of a state enterprise	36	7.3%
	Employee of a private enterprise	64	13.0%
	Self-employed /Freelancer	31	6.3%
	Other (including retired)	80	16.2%
E-health usage per month	1-2 times	424	85.8%
	3-4 times	34	6.9%
	5-6 times	4	0.8%
	More than 7 times	32	6.5%

Confirmatory Factor Analysis (CFA)

The technique for gauging latent variables is known as CFA (Byrne, 2013). The purpose of CFA was to determine whether or not a model was acceptable. Hence, it was crucial to assess all latent variables in the research before using a structural model (Perry et al., 2015). The skewness of the 8 variables varied from -0.4291 to 0.1262, while the kurtosis ranged from -0.60348 to 0.04798. The findings fell within the range of -2 to 2 (Byrne, 2013), indicating an adequate fit with a typical skewness curve. All values of skewness and kurtosis met the acceptance criteria. Meanwhile, the findings of multicollinearity for each set of potential variables was less than 0.800 (Barton & Peat, 2014), suggesting that there was no violation of multicollinearity.

The findings in Table 3 indicate that the constructs exhibited a coefficient of internal consistency that met the recommended criterion of a Cronbach's alpha (CA), i.e., a value of 0.70 or higher (Dikko, 2016). The factor loading for each variable was greater than 0.5 (Chau, 1997), with a t-value exceeding 1.96 and a p-value less than 0.05 (Hair et al., 2006). All constructs had a composite reliability (CR) value exceeding 0.6, and an average variance extracted (AVE) value exceeding 0.5, as reported by Fornell and Larcker (1981). To summarize, the statistical estimates were statistically significant.

The square root of AVE values is displayed in Table 4. Discriminant validity pertains to the extent to which a latent variable, labeled as A, could effectively distinguish itself from other hidden variables, such as B, C, and D (Farrell, 2010). This was evaluated using the statistical metric AVE. The study found that all the values of discriminant validity exceeded the inter-construct correlations, indicating that the discriminant validity was deemed acceptable.

Table 3. Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variables	Source of Questionnaire (Measurement Indicator)	No. of Items	CA	Factor Loading	CR	AVE
SI	Wang et. al. (2021)	4	0.865	0.715~0.823	0.866	0.618
FC	Tavares and Oliveira (2016)	4	0.864	0.734~0.821	0.866	0.618
RC	Guo et. al. (2013)	4	0.915	0.824~0.888	0.916	0.731
EE	Hoque and Sorwar (2017)	4	0.905	0.817~0.851	0.905	0.704
PS	Cimperman et. al. (2016)	4	0.914	0.828~0.858	0.914	0.728
PDT	Luo et. al. (2022)	3	0.859	0.795~0.875	0.862	0.676
PE	Venkatesh et. al. (2012)	3	0.857	0.814~0.823	0.859	0.670
BI	Zhang et. al. (2019)	3	0.860	0.786~0.842	0.861	0.674

Note: CA, CR and AVE.

Table 4. Discriminant Validity

Variables	Factor Correlations							
	SI	FC	RC	EE	PS	PDT	PE	BI
SI	0.786							
FC	0.347	0.786						
RC	-0.294	-0.350	0.855					
EE	0.245	0.368	-0.288	0.839				
PS	0.381	0.432	-0.367	0.331	0.853			
PDT	0.288	0.375	-0.346	0.344	0.426	0.822		
PE	0.463	0.407	-0.240	0.254	0.302	0.232	0.819	
BI	0.322	0.478	-0.420	0.499	0.516	0.501	0.385	0.821

Note: The diagonally-listed value is the AVE square roots of the variables

Structural Equation Model

SEM is a widely recognized statistical technique utilized for the analysis of multivariate data. It has garnered considerable attention in the field of marketing due to its particular suitability for the purpose of theory testing (Bagozzi, 1980). The evaluation of a single SEM is determined by assessing the goodness-of-fit between observed data and the model's predictions, as well as by examining the relationships between different variables. Table 5 presents the fitness of the model, where the values of the statistical indices from SEM are compared with the acceptable threshold. The indices and their corresponding values used to assess the goodness of fit are as follows: CMIN/DF=2.548, GFI=0.852, AGFI=0.825, CFI=0.936, NFI=0.900, TLI=0.930, and RMSEA=0.056. All index values met the acceptable requirement, thereby confirming the model's fitness.

Table 5. Goodness of Fit for the Structural Equation Model (SEM)

Index	Criterion	Statistical Value
$\chi 2$/df (CMIN/df)	<3 (Kline, 2023)	2.548
GFI	>0.85 (Sica & Ghisi, 2007)	0.852
AGFI	>0.80 (Sica & Ghisi, 2007)	0.825
CFI	>0.90 (Little, 2013)	0.936
NFI	≥ 0.90 (Hair et al., 2006)	0.900
TLI	>0.90 (Hu & Bentler, 1999)	0.930
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.056

Note: CMIN/DF=The ratio of the chi-square value to degree of freedom, GFI=goodness-of-fit index, AGFI=adjusted goodness-of-fit index, CFI=comparative fit index, NFI=normalized fit index, TLI=Tucker Lewis index and RMSEA=root mean square error of approximation

Source: constructed by the author

Testing of the Research Hypotheses

The importance of the association between variables was assessed based on the regression weights and R2 variances in the structural model. The findings demonstrate that all the study hypotheses were corroborated. Performance expectancy was most strongly predicted by social influence, with effort expectancy also contributing to behavioral intention, and facilitation conditions contributing to performance expectancy. Furthermore, the resistance to change resulted in a detrimental impact on behavioral intention. The causal correlations among the variables are displayed in Table 6.

The findings of the structural pathway analysis, as presented in Table 6 and Figure 2, are summarized as follows:

H1: The impact of social influence on performance expectancy was found to be positive, with a standardized path coefficient of 0.436 and a t-value of 8.647 ***. Performance expectancy was mostly impacted by social factors. Alarefi (2023) researched the factors influencing the behavioral intents of IoT healthcare devices (IoTHD) and concluded that a person's social influence was impacted by the people in their immediate environment. In other words, if those people were positive, the person would perceive performance expectancy favorably. The hypothesis was supported by previous empirical studies (Lu et al., 2005; Aggelidis & Chatzoglou, 2009; Or et al., 2011).

H2: The standardized path coefficient linking facilitation conditions and performance expectancy was 0.344, with a t-value of 7.036 ***. Facilitation conditions positively impacted performance expectancy. Therefore, H2 was confirmed. Rho et. al. (2015) investigated the characteristics that affected a consumer's willingness to use telemedicine services for improved diabetic mellitus management based on the UTAUT model. The findings showed that, via performance expectancy, facilitation conditions had an impact on behavioral intentions to use telemedicine services. Tsai (2021) also studied the connection between facilitating conditions and performance expectancy, which had a considerable impact on facilitating conditions and was positively tempered by performance expectancy. In addition, Zhang et. al. (2019) and Lai et. al. (2017) found that the facilitation condition affected performance expectancy.

H3: The hypothesis is validated, in that resistance to change negatively impacted behavioral intention, as indicated by a standardized path coefficient of -0.196 and a t-value of -4.401 ***. The impact of resistance to change on behavioral intention was the least compared to other variables, although it was still statistically significant ($p<0.001$). Bhattacherjee and Hikmet (2007) showed how resistance to change had a major detrimental effect on one's intention to use healthcare IT. Hoque and Sorwar (2017) also found that a consumer's behavioral intentions to use m-health services were significantly impacted by resistance to change. This corresponds to research conducted by Deng et. al. (2014), Chi et. al. (2020), and Dou et. al. (2017).

H4: The standardized path coefficient connecting effort expectancy and behavioral intention to use Internet medical services was 0.367 (t-value=7.688 ***), indicating the most significant impact on behavioral intention compared to resistance to change, perceived security, performance expectancy, and perceived disease threat. Alam et. al. (2018) studied the adoption of m-health in the healthcare system of Bangladesh using the UTAUT model, and found that effort expectancy had a significant influence on behavioral intention. Alkhalifah (2022) found that effort expectancy had a favorable impact on behavioral intentions to utilize m-health when examining the acceptance of m-health in Saudi Arabia. Consequently, H4 is supported and aligns with the findings of Pal et. al. (2018), Ofori et. al. (2021), and Diño and de Guzman (2015).

H5: The hypothesis is validated, given the positive impact of perceived security on the behavioral intention to use Internet medical services, with a standardized path coefficient of 0.308 and a t-value of 6.666 ***. When Shahbaz et. al. (2019) investigated how BDA was adopted in healthcare companies, they discovered that intention to use BDA was significantly predicted by perceived security. Furthermore, other research also found a significant relationship with health-related applications (Abdekhoda et al., 2019; Abd-Alrazaq et al., 2019; Zhao et al., 2018).

H6: The standardized path coefficient linking performance expectancy and behavioral intention was 0.223 with a t-value of 4.785 ***. H6, which had the smallest direct impact on behavioral intention, is validated. This finding shows that performance expectancy positively impacted on intention to use Internet medical services. Wang et. al. (2020) used a hybrid model based on UTAUT and technology task fit to interpret consumer acceptance of healthcare wearable devices. Their results indicate that performance expectancy positively affects a consumer's behavioral intention. Salgado et. al. (2020) demonstrated that the driver of intention to accept m-health had statistical relevance with performance expectancy. That said, there are still many research studies which found that performance expectancy had a significant impact on behavioral intention, such as Quaosar et. al. (2018), Azizi et. al. (2020), and Apolinário-Hagen et. al. (2018).

H7: Finally, the perceived disease threat positively impacted behavioral intention, as evidenced by the standardized path coefficient of 0.307 and a t-value of 6.491 ***. The findings of Zhang et. al. (2019) demonstrate that behavioral intention is directly impacted by perceived disease threat when using a smartphone application to control diabetes. Meanwhile, in order to better understand the psychological mechanisms which, determine how online health information-seeking behavior (OHISB) affects doctor-patient relationships, perceived disease severity and OHISB are positively associated (Luo et al., 2022). This finding is consistent with the studies of Tavares and Olivera (2016), Jayanti and Burns (1998), and Shah et. al. (2021).

Table 6. Hypothesis Testing Result of the Structural Model

Hypothesis		Standardized Path Coefficients (β)	t-value
H1	SI → PE	0.436	8.647 ***
H2	FC → PE	0.344	7.036 ***
H3	RC → BI	-0.196	-4.401 ***
H4	EE → BI	0.367	7.668 ***
H5	PS → BI	0.308	6.666 ***
H6	PE → BI	0.223	4.785 ***
H7	PDT → BI	0.307	6.491 ***

Note: ***=p<0.001; **=p<0.01; *=p<0.05.

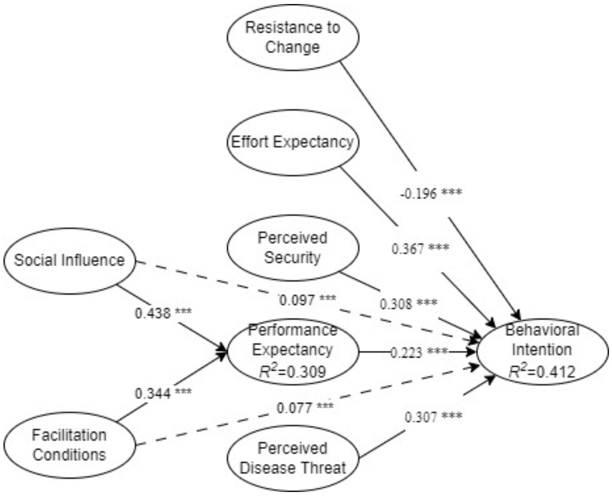

Figure 2. Revised Research Framework

Note: Solid line reported the Standardized Direct Coefficient with ***=p<0.001; Dash line reported the Standardized Indirect Coefficient with ***=p<0.001

Conclusions and Discussion

Conclusions

The findings validated the hypotheses that both the social influence and facilitation conditions had a favorable direct impact on performance expectancy, as well as a positive indirect impact on behavioral intention. Out of all the factors, social influence had the greatest impact on performance expectancy. Furthermore, the lack of willingness to adapt had a detrimental impact on the desire to act in a certain way. Effort expectancy, perceived security, and perceived disease threat positively influenced behavioral intention, with effort expectancy having the greatest direct impact on behavioral intention.

According to the findings of this study, Internet medical service providers may enhance the design and functionality of their platforms. Government departments may enhance their understanding of the key areas of public awareness, facilitate the widespread use of online services in China, and address the existing issue of limited and unequal distribution of medical resources.

This research provides more guidance for "Internet plus" by examining service quality. How can medical services effectively leverage the benefits, harness the limitless potential of the Internet, enhance patient experience during medical treatment, cultivate brand awareness of Internet medical services among patients, and establish a novel approach to healthcare? Not only can this type of research address the issue of limited access to doctors and alleviate the scarcity of medical resources, but it can also offer a clear path for traditional medical services to transition to the Internet.

Discussion

Social influence and facilitation conditions affect behavioral intention to use Internet medical services, both directly and indirectly, via performance expectancy. Thus, the expansion of Internet medical services is attributed to government policy, recommendations from others, and the perception of current trends. Specifically, the mean value of SI1 was lower than the other three measures of social influence, suggesting that the recommendations from medical experts were somewhat weak. If medical professionals had adequate training, their recommendations could assist patients in obtaining the necessary information, making it more likely for this particular set of patients to be receptive to using Internet-based medical services. It is also important to take advantage of the extensive support facilities and network environment of Internet medicine in order to enable easy access to services, in comparison with other technological applications. Compared to other items of facilitation conditions, participants expressed a persistent sense of inadequacy in terms of the resources available to them for utilizing Internet medical services. Consequently, there is an opportunity to exploit a greater number of smartphone applications, websites, and official accounts in a professional and thorough manner.

Effort expectancy significantly impacted the behavioral intention towards Internet medical services. The greater the proficiency in utilizing Internet medical services, the more likely individuals were to continue using these services. Hence, it is easier for people who are well-educated and possess fundamental IT skill to use the Internet medical service. On the other hand, it will be necessary to provide regular training programs to expand the target user group. This is particularly important for vulnerable people (e.g., lower-educated, older, lower income) who will need more opportunities to be well-trained.

Moreover, the impact of performance expectancy on behavioral intention was mediated. Participants reported that the Internet medical service had the potential to enhance productivity and expedite tasks, leading to a rise in their intention to use the service. However, these individuals had not yet experienced the complete effects of Internet medicine in their everyday life. To enhance the quality of daily life, it is recommended to establish dedicated sections on the Internet medical platform for nutritious meals, fitness tracking, and the popularization of medical science. This would enable individuals to access relevant medical information on a daily basis, in addition to seeking medical advice, and foster the habit of using the platform.

Finally, perceived security and perceived disease threat impacted behavioral intention. Hence, in designing Internet medical services, it is crucial to prioritize service security in order to instill a sense of safety among customers. The designers and implementers of the Internet medical service need to prioritize network security to guarantee the protection of personal and medical information from any potential leaks. On the other hand, it is also important for users to be aware of these security and privacy advancements. Meanwhile, people who have a long-term awareness of disease prevention or are worried about changes in their quality of life due to disease may have a relatively long-term intention to use Internet medicine. Often, individuals fail to recognize that the depletion of the workforce as a result of illness will have a profound impact on their entire professional trajectory. Hence, by establishing and promoting relevant exemplary case databases on the Internet medical platform, individuals might develop a heightened awareness of urgency when browsing the platform. This, in turn, should encourage them to utilize the Internet medical platform more frequently for illness prevention, triage, and treatment. Another area of research should focus on finding ways to surmount the natural resistance that individuals have toward change. One of the changes that people are most apprehensive about is altering the way they engage with others due to the prevalence of online healthcare. Hence, using video interview methods during online medical consultations and prescription processes could alleviate consumer apprehension, and enhance willingness to utilize these services.

Implications

Currently, the academic study on topics relating to "Internet medical service" is in the early stages. The research on patient behavioral intentions has lagged behind. Presently, the research in China about patient behavioral intention mostly centers on the development of an assessment index system. The aim is to derive theoretical models that align with the evaluation system.

For theoretical implications, numerous theoretical models have been proposed in previous studies pertaining to the acceptance of Internet medical services. The current empirical study utilized variables primarily derived from the UTAUT, supplemented by additional constructs from different theoretical frameworks, including perceived security, resistance to change, and perceived disease threat. The inclusion of these supplementary factors, which are considered from a physiological perspective and are connected to health issues, helped to elucidate the behavioral patterns of individuals. Resistance to change, which is considered a negative effect, could be assessed by evaluating the model from a different perspective. What is more, the integration of these constructs could enhance the explanatory capacity of the theoretical framework for the adoption of Internet medical services.

For practical implications, overestimation of the Internet's ability to disrupt conventional services of care was sometimes caused by a lack of knowledge about the Internet-informed patient. In addition to providing insights for the global expansion of Internet hospitals and connected matters affecting tailored digital health and patient-centered services, the findings of this study should contribute to the development of Internet medical services in China, which will help advance healthcare delivery on the Internet.

Limitation and Further Study

This study was based on previous research carried out with people who use Internet medical services. This article discussed research results on the creation of an Internet medical service, which was based on a questionnaire survey carried out among the citizens of Chengdu City. However, this study has research limitations and shortcomings due to several aspects.

Firstly, the research findings might have limited generalizability due to the small sample size and the small-scale nature of the study. It is important to note that this data set only captures the participants' intention to use the Internet medical service during the specific research period. Thus, the findings do not fully reflect actual willingness to use the service in the future. Therefore, there is potential for improvement at the data level.

Secondly, the conclusion of this article only pertains to the circumstances within a specific location. Hence, the author was unable to provide a comprehensive overview of the developmental progress across the entire country. In the future, it is recommended to broaden the scope of research on the Internet medical service to encompass additional regions of the country.

Thirdly, the predominant focus of this study was the viewpoints of individuals who utilized Internet medical services. Nevertheless, there is a lack of research on the viewpoints of organizations that offer Internet medical services. There is a scarcity of comprehensive research that examines the viewpoints of both supply and demand in a systematic manner. Those gaps in the research need to be filled.

References

Abd-Alrazaq, A., Bewick, B. M., Farragher, T., & Gardner, P. (2019). Factors Affecting Patients' use of Electronic Personal Health Records in England: Cross-sectional Study. *Journal of Medical Internet Research*, *21*(7), e12373-e12392.

Abdekhoda, M., Dehnad, A., & Khezri, H. (2019). The Effect of Confidentiality and Privacy Concerns on Adoption of Personal Health Record from Patient's Perspective. *Health and Technology*, *9*, 463-469.

Aggelidis, V. P., & Chatzoglou, P. D. (2009). Using a Modified Technology Acceptance Model in Hospitals. *International Journal of Medical Informatics*, *78*(2), 115-126.

Alam, M. Z., Hu, W., & Barua, Z. (2018). Using the UTAUT Model to Determine Factors Affecting Acceptance and Use of Mobile Health (mHealth) Services in Bangladesh. *Journal of Studies in Social Sciences*, *17*(2), 137-172.

Alarefi, M. (2023). Internet of Things in Saudi Public Healthcare Organizations: The Moderating Role of Facilitating Conditions. *International Journal of Data and Network Science*, *7*, 295-304.

Alkhalifah, T. (2022). A Structural Equation Modelling of Governing Factors Influencing Patient Acceptance of Mobile Health in Saudi Arabia: A Modified UTAUT Model. *International Journal of E-Services and Mobile Applications (IJESMA)*, *14*(1), 1-17.

Alpay, L. L., Henkemans, O. B., Otten, W., Rövekamp, T. A., & Dumay, A. C. (2010). E-health Applications and Services for Patient Empowerment: Directions for Best Practices in Netherlands. *Telemedicine and E-Health*, *16*(7), 787-791.

Ammenwerth, E. (2019). Technology Acceptance Models in Health Informatics: TAM and UTAUT. *Study Health Technology and Informatics*, *263*, 64-71.

Apolinário-Hagen, J., Menzel, M., Hennemann, S., & Salewski, C. (2018). Acceptance of Mobile Health Apps for Disease Management among People with Multiple Sclerosis: Web-based Survey Study. *JMIR Formative Research*, *2*(2), e119773-e119790.

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). Factors Affecting the Acceptance of Blended Learning in Medical Education: Application of UTAUT2 Model. *BMC Medical Education 20*, *376*, 1-9.

Bagozzi, R. P. (1980). *Causal Models in Marketing*. New York: Wiley.

Bandura, A. (1977). Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review*, *84*(2), 191.

Bandura, A., & Wessels, S. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), *Encyclopedia of human behavior* (Vol. 4, pp. 71-81). Academic Press.

Barton, B., & Peat, J. (2014). Medical Statistics: A guide to SPSS, Data Analysis and Critical Appraisal. New Jersey: John Wiley & Sons.

Baumeister, H., Seifferth, H., Lin, J., Nowoczin, L., Lüking, M., & Ebert, D. (2015). Impact of an Acceptance Facilitating Intervention on Patients' Acceptance of Internet-based Pain Interventions: A Randomized Controlled trial. T*he Clinical Journal of Pain*, *31*(6), 528-535.

Bhattacherjee, A., & Hikmet, N. (2007). Physicians' Resistance Toward Healthcare Information Technology: A Theoretical Model and Empirical Test. *European Journal of Information System*, *16*(6), 725-737.

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting Collaboration Technology Use: Integrating Technology Adoption and Collaboration Research. *Journal of Management Information Systems*, *27*(2), 9-54.

Burkhardt, M. E., & Brass, D. J. (1990). Changing Patterns or Patterns of Change: The Effects of a Change in Technology on Social Network Structure and Power. *Administrative Science Quarterly*, *35*(1), 104-127.

Byrne, B. M. (2013). Structural Equation Modeling with AMOS Basic Concepts, Applications, and Programming. New York: Routledge.

Caruth, G. D. (2013). Understanding Resistance to Change: A Challenge for Universities. *Turkish Online Journal of Distance Education*, *14*(2), 12-21.

Campbell, M. C., Inman, J. J., Kirmani, A., & Price, L. L. (2020). In times of trouble: A framework for understanding Consumers' Responses to Threats. *Journal of Consumer Research*, *47*(3), 311-326.

Champion, V. L., & Skinner, C. S. (2008). The Health Belief Model. *Health Behavior and Health Education: Theory, Research, and Practice*, *4*, 45-65.

Chau, P. Y. (197). Reexamining a Model for Evaluating Information Center Success Using a Structural Equation Modeling Approach. *Decision Sciences*, *28*(2), 309-334.

Chi, W. C., Lin, P. J., Chang, I., & Chen, S. L. (2020). The Inhibiting Effects of Resistance to Change of Disability Determination System: A Status quo Bias Perspective. *BMC Medical Informatics and Decision Making*, *20*(1), 1-8.

Chong, A. Y. L. (2013). Predicting M-Commerce Adoption Determinants: A Neural Network Approach, *Expert Systems with Applications*, *40*(2), 523-530.

Chopdar, P. K. (2022). Adoption of Covid-19 Contact Tracing App by Extending UTAUT Theory: Perceived Disease Threat as Moderator. *Health Policy and Technology*, *11*(3), 100651-100663.

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and Conformity. *Annual Review of Psychology*. *55*, 591-621.

Cimperman, M., Brenčič, M. M., & Trkman, P. (2016). Analyzing Older Users' Home Telehealth Services Acceptance Behavior-Applying an Extended UTAUT Model. *International Journal of Medical Informatics*, *90*, 22-31.

Compeau, D. R, & Higgins D. A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly*, *19*(2), 189-211.

Dash, S. P. (2020). The Impact of IoT in Healthcare: Global Technological Change & the Roadmap to a Networked Architecture in India. *Journal of Indian Institute of Science*, *100*(4), 773-785.

Deloitte. (2021). *Internet Hospitals in China: the new step into digital healthcare*. Retrieved from https://www2.deloitte.com/cn/en/pages/life-sciences-and-healthcare/articles/internet-hospitals-in-china-the-new-step-into-digital-healthcare.html

Deng, Z., Mo, X., & Liu, S. (2014). Comparison of the Middle-aged and Older Users' Adoption of Mobile Health Services in China. *International Journal of Medical Informatics*, *83*(3), 210-224.

Dikko, M. (2016). Establishing Construct Validity and Reliability: Pilot Testing of a Qualitative Interview for Research in Takaful (Islamic Insurance). *Qualitative Report, 21*(3), 521-528.

Diño, M. J. S., & de Guzman, A. B. (2015). Using Partial Least Squares (PLS) in Predicting Behavioral Intention for Telehealth Use Among Filipino Elderly. *Educational Gerontology*, *41*(1), 53-68.

Dou, K., Yu, P., Deng, N., Liu, F., Guan, Y., Li, Z., Ji, Y., Du, N., Lu, X., & Duan, H. (2017). Patients' Acceptance of Smartphone Health Technology for Chronic Disease Management: A Theoretical Model and Empirical Test. *JMIR MHealth and UHealth*, *5*(12), e177-e191.

Dwivedi, Y. K., Shareef, M. A., Simintiras, A. C., Lal, B., & Weerakkody, V. (2016). A Generalised Adoption Model for Services: A Cross-country Comparison of Mobile Health (m-health). *Government Information Quarterly*, *33*(1), 174-187.

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of Convenience Sampling and Purposive Sampling. *American Journal of Theoretical and Applied Statistics*, *5*(1), 1-4.

Fan, Y., Ma, Y., Zhang, Y., & Sun, C. (2022). A Retrospective Analysis of Internet-based Sharing Nursing Service Appointment Data. *Computational and Mathematical Methods in Medicine*, *2022*, 8735099-8735105.

Farrell, A. M. (2010). Insufficient Discriminant Validity: A Comment on Bove, Pervan, Beatty, and Shiu (2009). *Journal of Business Research*, *63*(3), 324-327.

Fishbein, M. & Ajzen, I. (1975). Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. Reading, Massachusetts: Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39-50.

Ghalandari, K. (2012). The Effect of Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions on Acceptance of e-banking Services in Iran: The moderating role of age and gender. *Middle East Journal of Scientific Research*, *12*(6), 801-807.

Guo, X., Sun, Y., Wang, N., Peng, Z., & Yan, Z. (2013). The Dark side of Elderly Acceptance of Preventive Mobile Health Services in China. *Electronic Markets*, *23*(1), 49-61.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (6th ed). Pearson Prentice Hall.

Hoque, B., & Sorwar, G. (2017). Understanding Factors Influencing the Adoption of m-Health by the Elderly: An Extension of the UTAUT Model. *International Journal of medical informatics*, *101*, 75-84.

Hsieh, P. J. (2016). An Empirical Investigation of Patients' Acceptance and Resistance Toward the Health Cloud: The Dual Factor Perspective. *Computers in Human Behavior*, *63*, 959-969.

Hu, L. T., & Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1-55.

Ito, A. (2019). Digital China: A Fourth Industrial Revolution with Chinese characteristics? *Asia-Pacific Review*, *26*(2), 50-75.

Jayanti, R. K., & Burns, A. C. (1998). The Antecedents of Preventive Health Care Behavior: An Empirical Study. *Journal of the Academy of Marketing Science*, *26*(1), 6-15.

Johnson, V. L., Woolridge, R. W., Wang, W., & Bell, J. R. (2019). The Impact of Perceived Privacy, Accuracy and Security on the Adoption of Mobile Self-Checkout Systems. *Journal of Innovation Economics & Management*, *1*(21), 221-247.

Khan, S., Umer, R., Umer, S., & Naqvi, S. (2021). Antecedents of Trust in Using Social Media for E-government Services: An Empirical Study in Pakistan. *Technology in Society*, *64*, 101400.

Kijsanayotin, B., Pannarunothai, S., & Speedie, S. M. (2009). Factors Influencing Health Information Technology Adoption in Thailand's Community Health Centers: Applying the UTAUT Model. *International Journal of Medical Informatics*, *78*(6): 404-416.

Kim, J. (2020). Impact of the Perceived Threat of COVID-19 on Variety-Seeking. *Australasian Marketing Journal*, *28*(3), 108-116.

Kline, R. B. (2023). *Principles and Practice of Structural Equation Modeling*. New York: Guilford Publications.

Kristianto, Y. E. (2021). Strategy of Technology Acceptance Model Utilization for Halodoc, A Telehealth Mobile Application with Task Technology Fit as Moderator Variable. *International Journal of Innovation Science and Research Technology*, *6*(8), 192-201.

Lai, C., Li, X., & Wang, Q. (2017). Students' Perceptions of Teacher Impact on Their Self-directed Language Learning with Technology Beyond the Classroom: Cases of Hong Kong and US. *Educational Technology Research and Development*, *65*, 1105-1133.

Lai, Y., Chen, S., Li, M., Ung, C. O. L., & Hu, H. (2021). Policy Interventions, Development Trends, and Service Innovations of Internet Hospitals in China: Documentary Analysis and Qualitative Interview Study. *Journal of Medical Internet Research*, *23*(7), e22330-e22343.

Li, W., Xu, A., Lu, M., Lin, G., Wo, T., & Xi, X. (2020). Influence of Primary Health Care Physicians' Perceived over Qualification on Turnover Intention in China. *Quality Management in Healthcare*, *29*(3), 158-163.

Li, Y., Yan, X., & Song, X. (2019). Provision of Paid web-based Medical Consultation in China: Cross-Sectional Analysis of Data from a Medical Consultation Website. *Journal of medical Internet research*, *21*(6), e12126-e12139.

Little, T. D. (2013). *Longitudinal Structural Equation Modeling*. New York: Guilford Press.

Lines, B. C., Sullivan, K. T., Smithwick, J. B., & Mischung, J. (2015). Overcoming Resistance to Change in Engineering and Construction: Change management factors for Owner Organizations. *International Journal of Project Management*, *33*(5), 1170-1179.

Lu, J., Yao, J. E., & Yu, C. S. (2005). Personal Innovativeness, Social Influences and Adoption of Wireless Internet Services Via Mobile Technology. *The Journal of Strategic Information Systems*, *14*(3), 245-268.

Luo, A., Yu, Z., Liu, F., & Xie, W. (2022). The Chain Mediating Effect of the Public's Online Health. *Frontiers in Public Health*, *10*, 874495.

Malterud, K., Siersma, V. D., & Guassora, A. D. (2016). Sample Size in Qualitative Interview Studies: Guided by Information Power. *Qualitative Health Research*, *26*(13), 1753-1760.

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet Banking Adoption: A Unified Theory of Acceptance and Use of Technology and Perceived Risk Application. *International Journal of Information Management*, *34*(1), 1-13.

NHC. (2021) *China's Internet Health Services Gathering Steam Amid COVID-19*. Retrieved from http://en.nhc.gov.cn/2021-08/24/c_85005.htm

Ofori, P. P., Antwi, E. A., & Asante-Oduro, A. (2021). The Behavioral Intention in Accessing Digital Healthcare Information on Social Media. *International Journal of Scientific Research in Science and Technology*, *8*(6), 510-521.

Or, C. K., Karsh, B. T., Severtson, D. J., Burke, L. J., Brown, R. L., & Brennan, P. F. (2011). Factors Affecting Home Care Patients' Acceptance of a Web-based Interactive Self-Management Technology. *Journal of the American Medical Informatics Association*, *18*(1), 51-59.

Pal, D., Funilkul, S., Charoenkitkarn, N., & Kanthamanon, P. (2018). Internet-of-things and Smart Homes for Elderly Healthcare: An End User Perspective. *IEEE Access*, 6, 10483-10496.

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory Factor Analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40.

Peikari, H. R., Shah, M. H., & Lo, M. C. (2018). Patients' Perception of the Information Security Management in Health Centers: The Role of Organizational and Human Factors. *BMC Medical Informatics and Decision Making*, *18*(102), 1-13.

Perry, J. L., Nicholls, A. R., Clough, P. J., & Crust, L. (2015). Assessing Model Fit: Caveats and Recommendations for Confirmatory Factor Analysis and Exploratory Structural Equation Modeling. *Measurement in Physical Education Exercise Science*, *19*(1), 12-21.

Quaosar, G. A. A., Hoque, M. R., & Bao, Y. (2018). Investigating Factors Affecting Elderly's Intention to Use m-health Services: An Empirical Study. *Telemedicine and E-Health*, *24*(4), 309-314.

Rana, A., Chakraborty, C., Sharma, S., Dhawan, S., Pani, S. K., & Ashraf, I. (2021). Internet of Medical Things-based Secure and Energy-efficient Framework for Health Care. *Big Data*, *10*(1), 18-33.

Ratten, V., & Ratten, H. (2007). Social Cognitive Theory in Technological Innovations. *European Journal of Innovation Management*, *10*(1), 90-108.

Rho, M. J., Kim, H. S., Chung, K., & Choi, I. Y. (2015). Factors Influencing the Acceptance of Telemedicine for Diabetes Management. *Cluster Computing*, *18*, 321-311.

Rosenstock, L. M. (1974). The Health Belief Model and Preventive Health Behavior. *Health Education Monographs*, *2*(4), 354-385.

Saha, P., & Nath, A. (2017). A Conceptual Framework of Festival Visitors' Behavioral Intentions. *In Management International Conference* at Monastier di Treviso (Venice), Italy on 24-27 May 2017, pp.275-284.

Salgado, T., Tavares, J., & Oliveira, T. (2020). Drivers of Mobile Health Acceptance and Use from the Patient Perspective: Survey Study and Quantitative Model Development. *JMIR Mhealth and Uhealth*, *8*(7), e17588-e17609.

Sarfaraz, J. (2017). Unified Theory of Acceptance and Use of Technology (UTAUT) Model-mobile banking. *Journal of Internet Banking and Commerce*, *22*(3), 1-20.

Starr, K. (2011). Principals and the Politics of Resistance to Change. *Educational Management Administration & Leadership*, *39*(6), 646-660.

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Hu, Y. (2019). Investigating the Adoption of Big Data Analytics in Healthcare: The Moderating Role of Resistance to Change. *Journal of Big Data*, *6*(1), 1-20.

Shah, S. K., Zhongjun, T., Sattar, A., & XinHao, Z. (2021). Consumer's Intention To purchase 5G: Do Environmental Awareness, Environmental Knowledge and Health Consciousness Attitude Matter?. *Technology in Society*, *65*, 101563.

Shen, C. W., Ho, J. T., Kuo, T. C., & Luong, T. H. (2017). Behavioral Intention of Using Virtual Reality in Learning. *In Proceedings of the 26th International Conference on World Wide Web Companion* at Republic and Canton of Geneva, Switzerland on April 3 - 7, 2017, pp. 129-137.

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the beck depression inventory-II: psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge Psychological Tests and Testing Research* (pp. 27-50). Nova Science Publishers.

Simkus, J. (2022). Convenience Sampling: Definition, Method and Examples. *Retrieved from https://www.simplypsychology.org/convenience-sampling.html*

Sobti, N. (2019) Impact of Demonetization on Diffusion of Mobile Payment Service in India. *Journal of Advances in Management Research*, *16*(4), 472-497.

Soper, D. (2006). Calculator: A-Priori sample size for structural equation models. Daniel Soper.

Spears, N., & Singh, S. N. (2004). Measuring Attitude Toward the Brand and Purchase Intentions. *Journal of Current Issues & Research in Advertising*, *26*(2), 53-66.

Srivastava, J., Routray, S., Ahmad, S., & Waris, M. M. (2022). Internet of medical things (IoMT)-Based Smart Healthcare System: Treads and Progress. *Computational intelligence and Neuroscience*, *2022*, 7128113-7128129.

Tavares, J., & Oliveira, T. (2016). Electronic Health Record Patient Portal Adoption by Health Care Consumers: An Acceptance Model and Survey. *Journal of Medical Internet Research*, *18*(3), e49-e69.

Thomson, P. (2008). Head Teacher Critique and Resistance: A Challenge for Policy, and for Leadership/management Scholars. *Journal of Educational Administration and History*, *40*(2), 85-100.

Tomaka, J., Blascovich, J., Kelsey, R. M., & Leitten, C. L. (1993). Subjective, Physiological, and Behavioral Effects of Threat and Challenge Appraisal. *Journal of Personality and Social Psychology*, *65*(2), 248-260.

Tsai, L. L. (2021). Evaluating the Effects of Facilitating Conditions and Usage Experience on Mobile Payment. *International Journal of Information Systems in the Service Sector (IJISSS)*, *13*(4), 88-106.

Utomo, P., Kurniasari, F., & Purnamaningsih, P. (2021). The Effects of Performance Expectancy, Effort Expectancy, Facilitating Condition, and Habit on Behavior Intention in Using Mobile Healthcare applications. *International Journal of Community Service and Engagement*, *2*(4), 183-197.

Venkatesh, V., Morris, M. G., Davis, G. B, & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157-178.

Wang, H., Tao, D., Yu, N., & Qu, X. (2020). Understanding Consumer Acceptance of Healthcare Wearable Devices: An Integrated Model of UTAUT and TTF. *International Journal of Medical Informatics*, *139*, 104156.

Wang, J., Yang, Y., Li, H., & van Aalst, J. (2021). Continuing to Teach in a Time of Crisis: The Chinese Rural Educational System's Response and Student Satisfaction and Social and Cognitive presence. *British Journal of Educational Technology*, *52*(4), 1494-1512.

Warshaw, P. R., & Davis, F. D. (1985). Disentangling Behavioral Intention and Behavioral Expectation. *Journal of Experimental Social Psychology*, *21*(3), 213-228.

Wilson, E.V., & Lankton, N. K. (2009). Predicting Patients use of Provider-Delivered e-health: The Role of Facilitating Condition. *Patient-Centered E-Health*. IGI Global, 217-229.

Xu, X., Cai, Y., Wu, S., Guo, J., Yang, L., Lan, J., Sun, Y., Wang, B., Wu, J., Wang, T., Huang, S., Lin, Y., Hu, Y., Chen, M., Gao, X., & Xie, X. (2021). Assessment of Internet hospitals in China during the COVID-19 pandemic: national cross-sectional data analysis study. *Journal of Medical Internet Research*, *23*(1), e21825-e21836.

Zhang, Y., Liu, C., Luo, S., Xie, Y., Liu, F., Li, X., & Zhou, Z. (2019). Factors Influencing Patients' Intentions to Use Diabetes Management Apps Based on an Extended Unified Theory of Acceptance and Use of Technology Model: Web-based Survey. *Journal of Medical Internet Research*, *21*(8), e15023-e15039.

Zhang, Z. K., Cho, M. C. Y., Wang, C. W., Hsu, C. W., Chen, C. K., & Shieh, S. (2014). IoT Security: Ongoing Challenges and Research Opportunities. *In 2014 IEEE 7th international conference on service-oriented computing and applications*, 230-234.

Zhao, Y., Ni, Q., & Zhou, R. (2018). What Factors Influence the Mobile Health Service Adoption? A Meta-Analysis and the Moderation Role of Age. *International Journal of Information Management, 43*, 342-350.

Zhou, T. (2008). Exploring Mobile User Acceptance Based on UTAUT and Contextual Offering. *In 2008 International Symposium on Electronic Commerce and Security* at Guangzhou, China on August 3, 2008. pp. 241-245.