Journal of Organizational and End User Computing
Volume 34 • Issue 4

An Investigation of Patient Decisions to Use eHealth:
A View of Multichannel Services

Suli Zheng, China Jiliang University, China

Po-Ya Chang, National Taipei University of Nursing and Health Sciences, Taiwan

Jiahe Chen, Western Sydney University, Australia

https://orcid.org/0000-0003-3466-3016

Yu-Wei Chang, National Taichung University of Science and Technology, Taiwan

Hueng-Chuen Fan, Tungs' Taichung Metroharbor Hospital, Taiwan & National Chung Hsing University, China & Jen-Teh Junior College of Medicine, Taiwan

ABSTRACT

eHealth service has received increasing attention. Patients can consult online doctors via the internet and then physically visit the doctors for further diagnosis and treatments. Although extant research has focused on the adoption of eHealth services, the decision-making process from online to offline health services remains unclear. This study aims to examine patients' decisions to use online and offline health services by integrating the extended valence framework and the halo effect. By analyzing 221 samples with online consultation experiences, the results show that trust significantly influences perceived benefits and perceived risks, while trust, perceived benefits, and perceived risks significantly influence the intention to consult. The intention to consult positively influences the intention to visit. Considering the moderating effects of payment types, the influence of perceived risks on the intention to consult is larger for the free group than for the paid group. The findings are useful to better understand patients' decisions to use eHealth.

KEYWORDS

eHealth, Extended Valence Framework, Halo Effect, Online Health Consultation, Payment Types

INTRODUCTION

With the development of the healthcare industry and high-speed internet facilities, eHealth has been developing rapidly worldwide. eHealth can encompass a range of services, including telehealth, telemedicine, mHealth, electronic medical records, or other health IT services. When health applications are linked to mobile devices, patients can consult online doctors via mobile phones, and doctors can treat their patients remotely. As the number of health internet users is growing rapidly, the global eHealth market is expected to grow from USD 40.82 billion in 2017 to 132.35 billion by 2023 (marketsandmarkets.com, 2018). Governments and businesses in China, India, and Australia contribute to the development of the eHealth market.

DOI: 10.4018/JOEUC.289433

Online health consultation is a type of eHealth service in which communication between patients and doctors is offered via the internet. Patients can consult online doctors about their illnesses, and doctors can provide diagnoses, treatment plans and even prescriptions via the internet. If necessary, a patient can physically visit a doctor for further diagnosis and treatment after consulting the online doctor. Contrary to the traditional direct visit with a doctor, online health consultations help patients save considerable time and offer convenience (Chang et al., 2019). In particular, during the coronavirus disease 2019 (COVID-19) pandemic, online health consultations can help reduce the risk of cross-infection for patients with mild illnesses.

Although eHealth is playing an increasingly important role in the COVID-19 pandemic, the adoption rate of online health consultations was relatively low in China. According to a research report, 390 million Chinese people have used eHealth services, including online appointments, health information seeking, and patient-centered communication. Among eHealth users, less than half (47.6%) used online health consultations, accounting for only a quarter of the Chinese population (LeadLeo, 2020). Compared with more than half of Americans who used online health consultations, the low adoption rate limits the development of the eHealth industry (Gong et al., 2019). Therefore, understanding the factors that affect patients' use of online health consultations seems more important than ever.

Online health consultation services are beneficial to patients, but online health services also introduce privacy risks for patients, who disclose personal information (i.e., medical consultations, medical treatments, and medicine prescriptions) on online health platforms. When patients worry that their personal information may be hacked via the internet and even be misused by unknown institutions, they may refuse to use online services. Since risks may decrease patients' intentions to adopt technology, trust is proposed to be an effective way to mitigate the perception of risks (Gong et al., 2019; Hong et al., 2019; Lee et al., 2018; Li et al., 2020). Trust is included in the proposed model to be the antecedent of perceived benefits and perceived risks.

Although the extant research has increasingly focused on the adoption of eHealth services, such as health information systems, online seeking services, and online health forums (Chang et al., 2016; Cho, 2016; Dünnebeil et al., 2012; Hong et al., 2021; Lai & Wang, 2015; Li & Wang, 2019; Turan et al., 2015), the research on online health consultations is very limited. Since most of these studies have examined the behavioral intention or intention to use online services, the decision-making process from online to offline health services remains unclear. In addition, patients exhibit different degrees of behavioral intentions for different payment types (e.g., free or paid consultation). To the best of our knowledge, no prior studies have investigated the moderating effects of payment types on online and offline health services. Therefore, this study aims to fill the gaps by understanding patients' decision-making processes in groups of different payment types.

Since the extended valence framework can explain consumer decision-making patterns based on perceived risks and perceived benefits (Peter & Tarpey, 1975), this theory is applied to examine the relationship between trust, benefits, and risks in the context of online health consultations. This study further incorporates service quality as the external variable of the extended valence framework, and investigates patient behaviors from online to offline channels based on the halo effect. Since the halo effect has been extensively validated on multiple channels (Thorndike,1920), it can help illustrate the relationship between the intention to consult and visit doctors. In particular, our research questions are as follows:

1. What are the factors affecting patients' intentions to use online and offline health services?
2. How do patients' intentions to use online and offline health services influence each other?
3. How do payment types moderate patients' decision-making processes regarding health services?

By answering these research questions, this study helps doctors and online health service providers better understand patients' decisions to use online and offline health services. The research makes three contributions. First, the proposed model draws from the extended valence framework and the halo effect. This study focuses on the factors that affect patients' intentions to use online and offline health services. Second, we extend the extant research that focused on the adoption of eHealth services to the intention to use offline health services. Third, the moderating effects of payment types are further identified and analyzed in eHealth.

The remainder of this study is organized as follows. Section 2 reviews the literature on eHealth and introduces the theoretical foundations used in this study, including the extended valence framework and the halo effect. Section 3 presents the research model and hypotheses. Section 4 describes the research methodology, followed by the results of the data analysis in Section 5. Section 6 discusses the findings of this study. Section 7 presents the theoretical and practical contributions. Conclusions and limitations are presented in the last section.

LITERATURE REVIEW

eHealth

eHealth can be referred to as the use of information and communication technologies (ICT) for health services and information. The World Health Organization (WHO) defines eHealth as "the cost-effective and secure use of information and communication technologies in support of the health and health-related fields including healthcare, health surveillance and health education, knowledge and research." The European Commission defines eHealth as "the use of modern information and communication technologies to meet needs of citizens, patients, healthcare professionals, healthcare providers, as well as policy makers."

eHealth can also include digital health applications on mobile devices, such as mobile phones, tablets, personal digital assistants, and the wireless infrastructure. The mode is also referred to as mobile health (mHealth) (Hamida et al., 2015). Online health consultation is a common eHealth service and can allow patients to use mobile devices to access to medical consultations with online doctors. Doctors can also deliver drug prescriptions to their patients via the internet. Since online health consultations can help to improve health quality, gain convenience, and reduce healthcare costs, online health services have become very popular in recent years.

Some researchers have focused on the adoption of online health consultations (Chang et al., 2019; Xin et al., 2020; Le et al., 2019). From the cost-benefit perspective, scholars have investigated the factors that influence the adoption of online health consultations (Gong et al., 2019; Hong et al., 2019; Li et al., 2020). The results showed that risk and benefit factors contribute to patients' intentions to use health services. Wang et al. (2020) and Li et al. (2018) found that trust plays a crucial role in determining patients' intentions to use online health consultations. In the research of Arfi et al. (2021) and Arfi et al. (2021), they focused on human-technology interactions to understand the adoption of eHealth services.

Most of the existing literature has examined the determinants of the adoption of online health consultations from an online perspective. In fact, patients may go to hospitals for treatment after consulting online doctors. The relationship between online consultations and offline visits remains unclear in eHealth. Thus, this study focuses on patients' decision-making processes from online to offline health services to bridge the research gap. In addition, based on different payment types (free and paid consultation), different groups of patients may have different perceptions and behavioral intentions. Drawing on the extended valence framework and the halo effect, we explore the factors that affect patients' intentions to use online and offline health services. The moderating effects of payment types are further identified and analyzed.

Extended Valence Framework

The valence framework proposed by Peter and Tarpey (1975) originated from the economics and psychology literature. This framework was used to explain consumer decision-making patterns based on perceived risks and perceived benefits. Consumers perceive products or services as having both positive attributes (i.e., perceived benefits) and negative attributes (i.e., perceived risks). After consumers maximize the positive attributes and minimize the negative attributes, they balance two attributes to maximize the net valence (Peter & Tarpey, 1975). The valence framework has been used to examine consumer behaviors in e-commerce contexts (Lee et al., 2018; Lu et al., 2011; Mou et al., 2020; Ozturk et al., 2017).

Given the important role of trust in the success of e-commerce, the extended valence framework proposed by Kim et al. (2009) integrated trust into the original valence framework. The extended valance framework suggests trust as the antecedent of perceived benefits and perceived risks. According to the extended valence framework, trust has an impact on perceived benefits and perceived risks. In addition, trust, perceived benefits, and perceived risks have direct effects on consumer behavior. The extended valence framework has been applied to explain consumer behaviors in different contexts, such as eHealth services (Gong et al., 2019; Hong et al., 2019; Ren et al., 2019), Fintech (Ryu, 2018), AI (Bedué & Fritzsche, 2021), and information systems (Wimmer & Yoon, 2017).

In addition to the extended valence framework, several theories have also been adopted to understand consumer behaviors in eHealth. Gong et al. (2019) integrated the extended valence framework and the theory of reasoned action (TRA) to investigate patients' adoption of online health consultations. Based on the unified theory of acceptance and use of technology (UTAUT), scholars have integrated trust, perceived risks, and financial costs to extend UTAUT to investigate customers' adoption of the internet of Things (IoT) in eHealthcare (Arfi et al., 2021; Arfi et al., 2021). Customers' gender and age play moderators in their research models. Li et al. (2020) adopted the theory of planned behavior (TPB) to understand patients' intentions to use online inquiry services. The results showed that the risks from and convenience of online services influence patients' intentions. Table 1 summarizes the theories and frameworks used in eHealth.

The purpose of this study is to better understand how to increase patients' intentions to use online and offline health services. Although patients can reduce costs, save time, and obtain better access to knowledge from online services, they may worry whether doctors properly collect, store and use their personal information. The benefits and risks might be considered positive and negative valences of using online health consultations. Additionally, trust can be used to increase perceived benefits and reduce perceived risks. Thus, this study posits that the extended valence framework can provide a robust theoretical foundation to examine the relationships between trust, perceived benefits, perceived risks, and behavioral intentions in the context of online health consultations.

Since online health consultation is the application of e-commerce in eHealth, service quality should be incorporated into the proposed research model. Previous research has indicated that service quality is also a significant determinant of behavioral intentions (Lee et al., 2018; Zhou, 2014; Zhou et al., 2010). In particular, patients evaluate the service performance provided by online doctors, such as doctors' responses, consultation processes, and doctor-patient interactions (Chang et al., 2019; Xin et al., 2020). Service quality is important for increasing patients' trust in doctors, which in turn determines whether to continue to consult and visit the doctors. However, the extended valence framework did not pay attention to the relationship. Therefore, this study incorporates service quality as the external variable of the extended valence framework to examine the relationship between service quality and trust.

Table 1. Previous studies on eHealth

Previous studies	Positive valence	Negative valence	Theory and framework	Research issue
Gong et al. (2019)	Perceived benefit	Perceived risk	The extended valence framework	Online healthcare services
Hong et al. (2019)	Perceived benefit	Perceived risk	The extended valence framework, theory of planned behavior	Online healthcare services
Ren et al. (2019)	Learning benefits, functional benefits, social benefits, personal integrative benefits	Cognitive costs, executional costs	Valence framework	Health information seeking
Arfi et al. (2021)	Performance expectancy	Perceived risk	United theory of acceptance and use of technology	eHealth services
Arfi et al. (2021)	Performance expectancy	Perceived risk, financial cost	United theory of acceptance and use of technology	eHealth services
Li et al. (2020)	Perceived convenience, perceived outcome	Perceived information risk, perceived medical risk	Theory of planned behavior	Online inquiry services

Halo Effect

The halo effect proposed by Thorndike (1920) refers to a cognitive bias in which an observer's overall impression of a person, company, brand, or product influences the observer's perceptions of that entity's characteristics. If an observer likes one characteristic of the entity, he/she will have a positive perception of other characteristics. If an observer dislikes one characteristic of the entity, he/she will have a negative perception of other characteristics. Previous studies have applied the halo effect concept to various domains, such as psychology, social psychology, organizational behavior, and marketing (Cowan & Little, 2013; Dunham & Burt, 2011; Zhang et al., 2014).

The halo effect has been applied to explain the relationship between online and offline channels in multichannel contexts. Jin et al. (2010) applied the halo effect to investigate online and offline operations. They found that the characteristics of and satisfaction with offline channels increase the satisfaction with and loyalty to online channels. Kwon and Lennon (2009) investigated the effects of a multichannel retailer's offline and online brand images on consumers' online loyalty. The results revealed that if a retailer has a positive offline brand image, its online brand image will be more positive. The effect is consistent with the halo effect concept.

Previous studies on eHealth have adopted the halo effect to explain patients' intentions to use online and offline health services. Chang et al. (2019) integrated online and offline health services based on the halo effect. The results showed that doctor-patient online interactions can motivate patients' continued intentions to consult doctors, thereby driving their intention to visit doctors. Xin et al. (2020) found that online doctor-patient interactions influence the use of online consultation services and offline medical treatment. Consistent with the halo effect, the findings showed that patients' online consultation intentions affect their face-to-face consultation intentions.

Based on these previous studies, the experience with one channel can serve as a halo effect, which affects the evaluation of another channel. If an individual has a good impression of a certain entity while experiencing the service provided by a certain channel, he/she may also have a higher evaluation of other channels of the entity and be willing to experience the services provided by other channels. Because patients who intend to consult online doctors are likely to further visit the doctors, online channels can be extended to offline channels. The impacts of the online consultation intention should also be considered when investigating the offline visit intention in multichannel settings. Therefore, this study posits that the intention to consult online doctors may be an important source of the halo effect.

RESEARCH MODEL AND HYPOTHESES

Service quality is defined as patients' overall service performance associated with online consultation services. Service quality can be measured from multiple characteristics, such as assurance, empathy, and responsiveness. Doctors provide patients with assured, timely, and attentive services during online consultations, leading to a higher intention to consult doctors. In e-commerce contexts, service quality reflects the motivation to increase consumers' trust in suppliers. After experiencing actual services, consumers are able to easily evaluate their level of trust in suppliers. Past research has also suggested that service quality plays a critical role in determining consumers' trust in suppliers (Lee et al., 2018; Zhou, 2014; Zhou et al., 2010). If the services provided by doctors can meet patients' needs and reflect excellent quality, patients are likely to have a higher level of trust in doctors. Thus, this study hypothesizes:

H1: Service quality positively affects trust.

Trust is considered to be an important factor influencing perceived benefits, perceived risks, and behavioral intentions. Trust in this study refers to patients' expectations about the motives and behaviors of online doctors. When patients have a high level of trust in doctors, they believe that doctors are less likely to behave opportunistically. Although patients may be concerned about privacy and security risks, they still provide and disclose personal information. On the other hand, when patients have a high level of trust in online doctors, they believe that the doctors will endeavor to realize patients' interests (e.g., commitments to the consultation quality). Thus, trust can help reduce uncertainty and increase awareness of potential benefits (Gong et al., 2019; Hong et al., 2019; Lee et al., 2018; Li et al., 2020).

According to the extended valence framework, trust directly and indirectly influences consumers' decision-making processes thorough perceived benefits and perceived risks. Trust determines whether a consumer has a positive attitude toward shopping and online purchase intention in e-commerce contexts (Jarvenpaa et al., 2000). Trust may not only facilitate the transaction process but may also promote behavioral intentions (Pavlou, 2003; Zhou, 2013). In eHealth, trust reflects patients' willingness to take risks to meet their health needs. Even if patients account for privacy risks, patients who have a high level of trust in doctors are likely to consult online doctors. The existing evidence has suggested that trust plays an important role in determining their intention to use eHealth services (Arfi et al., 2021; Gong et al., 2019; Hong et al., 2019; Li et al., 2018; Li & Wang, 2019; Wang et al., 2020). Thus, this study hypothesizes:

H2: Trust positively affects perceived benefits.
H3: Trust negatively affects perceived risks.
H4: Trust positively affects the intention to consult.

As a component of the extended valence framework, perceived benefits in this study are defined as the perceived utility associated with online consultation services. Online health consultation services can help patients considerable time and offer convenience, which have been identified as potential benefits compared with traditional offline health services (Gong et al., 2019). Patients must wait in lines for long periods when going to hospitals for treatment. The costs for offline health services are higher than those for online health services. Moreover, patients can gain a wider range of medical knowledge from doctors via the internet. When patients are able to benefit from the advantages, they will be more likely to consult online doctors. Empirical studies on eHealth have shown that perceived benefits have a positive effect on behavioral intention (Gong et al., 2019; Hong et al., 2019; Li et al., 2020; Ozturk et al., 2017). Thus, this study hypothesizes:

H5: Perceived benefits positively affect the intention to consult.

As another important component of the extended valence framework, perceived risks in this study are defined as privacy and security risk concerns associated with online consultation services. Patients are required to disclose personal information and diseases, which is a major concern. Since the information is transmitted to doctors through online health platforms, patients may worry that online health service providers behave opportunistically. For example, personal information or medical records could be misused by unknown individuals or companies or be disclosed to hospital institutions. When patients with high risk beliefs feel greater uncertainty, they tend to reduce their intention to consult online doctors. Several studies have suggested that perceived risks negatively affect behavioral intention in different e-commerce contexts (Gong et al., 2019; Lee et al., 2018; Lu et al., 2011; Mou et al., 2020; Ozturk et al., 2017; Ryu, 2018). Thus, this study hypothesizes:

H6: Perceived risks negatively affect the intention to consult.

According to the halo effect, consumers' behavioral intentions to use one channel influences their purchase decisions toward another channel in multichannel settings (Yang et al., 2011). After experiencing online services, a patient who need further treatment is able to evaluate the option of going to a hospital to receive additional treatment. If a patient has a good impression of the doctor, he/she is more likely to consult and visit the doctor. A satisfactory online consultation service contributes to enhancing the patient's willingness to visit the same doctor offline for further treatment. In contrast, an unsatisfactory online consultation service results in the patient's reluctance to visit the doctor. Past research on eHealth has verified the relationships between online and offline health services based on the halo effect (Chang et al., 2019; Xin et al., 2020; Le et al., 2019). Thus, this study hypothesizes:

H7: The intention to consult positively affects the intention to visit.

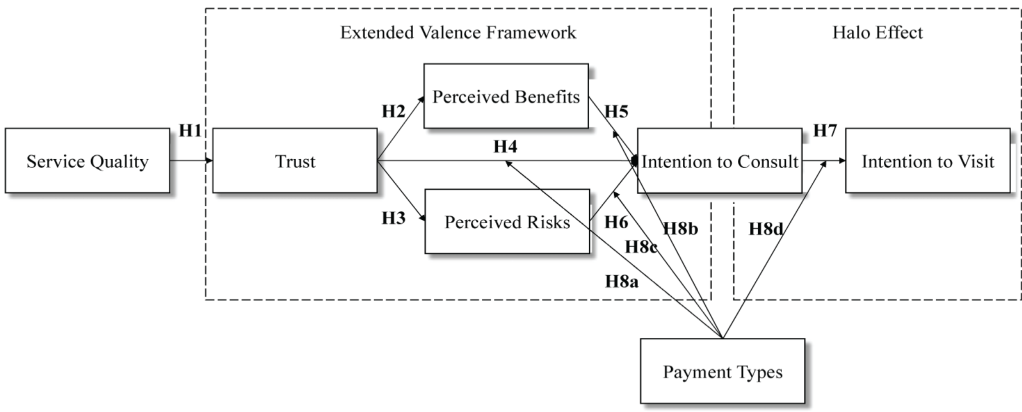
The adoption of a product or service depends not on the attributes of the product or service itself but also on the characteristics of consumers. Previous studies have posited that individual differences determine the use of new technologies (Arfi et al., 2021; Arfi et al., 2021; Chen et al.., 2020; Hong et al., 2019; Ryu, 2018). Since patients' propensity to pay results in different expectations for online health consultations, their perceptions of benefits and risks lead to different behavioral intentions (Hong et al., 2019). This study classifies payment types into two categories, i.e., free and paid groups. The free group refers to patients who have not paid to consult doctors; the paid group refers to patients who paid to consult doctors.

The influences of benefits and risks on the intention to consult doctors are larger for the free group than for the paid group. For the free group, patients directly saved on consulting costs for online health consultations. Thus, they receive more potential benefits than the paid group. In addition, the free group, who is sensitive to monetary costs, may also have a greater reaction to risks than those in the other group. Thus, it is expected that the higher the risk is, the lower the intention to consult doctors. On the other hand, because the paid group has paid for online health services, they have a higher level of trust and a more positive attitude toward online and offline health services than the free group. The relationship between the intention to consult doctors and the intention to visit doctors is stronger for the paid group than for the free group. Therefore, this study hypothesizes:

H8a: The effect of trust on the intention to consult is greater for the paid group than for the free group.
H8b: The effect of perceived benefits on the intention to consult is greater for the free group than for the paid group.
H8c: The effect of perceived risks on the intention to consult is greater for the free group than for the paid group.
H8d: The effect of the intention to consult on the intention to visit is greater for the paid group than for the free group.

The research model of this study is shown in Figure 1.

Figure 1. Research model



RESEARCH METHODOLOGY

Instrument Development

The research model was tested using a survey that includes the following measures. The items for service quality were adapted from DeLone and McLean (2003) to measure patients' perceptions of consulting service performance. The items for trust were adapted from Jarvenpaa et al. (2000) to reflect patients' beliefs in the motives and behaviors of doctors. The items for perceived benefits were adapted from Lee (2009) to measure the utility associated with online health consultations. The items for perceived risks were adapted from Dinev and Hart (2006) to measure the potential uncertainty associated with online health consultations. The items for the intention to consult and the intention to visit were adapted from Venkatesh et al. (2003) to measure patients' decisions to use online and offline health services. All items were ranked on a seven-point Likert scale (see Table 8 in the Appendix for full measurement items).

Data Collection

This study collected data from patients on the Good Doctor website (i.e., haodf.com), which is the oldest and largest online health platform in China. The Good Doctor website provides various eHealth services, including online consultation, remote diagnosis, a healthcare library and knowledge. The Good Doctor website allows patients to consult online doctors and then patients can make reservations with doctors for offline health services. As a result, patients' willingness to visit doctors can be investigated when they have had online consultation experiences.

We contacted the doctors of the Good Doctor website and asked if they were willing to participate in the research. A total of 10 doctors voluntarily provided assistance and distributed online questionnaires to their patients who had online consultation experiences. We obtained 221 valid responses. The respondents were classified into free- and paid groups (115 and 106). Regarding the free groups, 67 were male (63.8%), 55 were between 26 and 35 (52.4%), 73 had a bachelor's degree (69.5%), and 43 had incomes between 3001 and 6000 yuan per month (37.4%). Regarding the paid group, 56 were male (48.3%), 63 were between 26 and 35 (54.3%), 72 had a bachelor's degree (62.1%), and 41 had incomes between 3001 and 6000 yuan per month (38.6%). The demographic information of the respondents is presented in Table 9 in the Appendix.

Data Analysis

This study conducted SPSS and partial least squares (PLS) analysis to evaluate the collected data. SPSS was used to assess the demographic information of the respondents. Compared with covariance-based structural equation modeling (SEM), PLS-SEM supports the analysis of complex models composed of many latent and measured variables. PLS-SEM also allows for the use of non-normal distributions and small sample sizes (Chin, 1998; Gefen & Straub, 2005). Thus, PLS-SEM was chosen to examine the measurement and structural models in this study.

Before conducting the PLS-SEM analysis, Harman's single factor test was used to evaluate common method variance (CMV). The measurement model was used to evaluate the reliability, convergent validity, and discriminant validity (Khan et al., 2019; Shiau & Chau, 2016). The discriminant validity depends on Fornell-Larcker criterion and variance inflation factor (VIF) (Hair et al., 2009). The structural model was used to test the research hypotheses and model. The path coefficient and significance level of each hypothesis and the variance explained (R^2) were examined. Finally, to further compare different groups of free and paid respondents, we conducted PLS multi-group analysis (PLS-MGA) and used the measurement invariance technique to analyze the measurement invariance of composite models (MICOM) (Henseler et al., 2016; Huang & Shiau, 2017).

RESULTS

Common Method Variance

This study used Harman's single factor technique to test CMV. If the variance explained by a single factor exceeds 50%, there may be common method bias (Podsakoff & Organ, 1986; Shiau et al., 2020). SPSS was used to conduct the principal component analysis. The results showed that the first and largest factor explains 49% of the total variance, which is lower than 50%. Therefore, common method bias is not a main concern in this study.

Measurement Model

First, this study conducted a confirmatory factor analysis (CFA) to test the measurement model. Reliability was assessed using Cronbach's alpha. As listed in Table 2, Cronbach's alpha for each construct ranges from 0.77 to 0.95, which are larger than the threshold of 0.7. Convergent validity was assessed using factor loading, composite reliability (CR), and average variance extracted (AVE) (Gefen et al., 2000). Table 2 lists the factor loadings for all items range from 0.73 to 0.96, which are larger than the threshold of 0.7; CR for each construct ranges from 0.86 to 0.97, which exceed the threshold of 0.7; and AVE for each construct ranges from 0.60 to 0.91, which are above the threshold of 0.5.

Second, this study compared the square root of the AVE with the respective constructs to examine the discriminant validity. Table 3 lists that the square root of AVE for each construct is higher than the correlations between other constructs. VIF static was computed to test the level of multicollinearity

Table 2. Reliability

Construct	Factor Loading	Mean	S.D.	CR	Cronbach's alpha	AVE
Service Quality (SQ)	0.80	6.27	0.77	0.86	0.77	0.60
	0.80					
	0.73					
Trust (TR)	0.93	6.43	0.76	0.93	0.90	0.83
	0.91					
	0.89					
Perceived Benefits (PB)	0.90	6.34	0.86	0.93	0.89	0.81
	0.91					
	0.89					
Perceived Risks (PR)	0.94	3.75	1.63	0.96	0.94	0.89
	0.95					
	0.95					
Intention to Consult (IC)	0.96	6.00	1.13	0.97	0.95	0.91
	0.95					
	0.95					
Intention to Visit (IV)	0.91	6.28	0.93	0.95	0.91	0.85
	0.93					
	0.93					

Table 3. Inter-construct correlations

	SQ	TR	PB	PR	IC	IV
SQ	0.77					
TR	0.75	0.91				
PB	0.70	0.70	0.90			
PR	-0.36	-0.31	-0.35	0.94		
IC	0.62	0.53	0.63	-0.35	0.95	
IV	0.61	0.57	0.61	-0.28	0.61	0.92

between constructs (Hair et al., 2009; Mathieson et al., 2001). Table 4 shows that the VIF values range from 1 to 2.06, which are below the cut-off threshold of 10. Thus, we support results for the reliability, convergent validity, and discriminant validity.

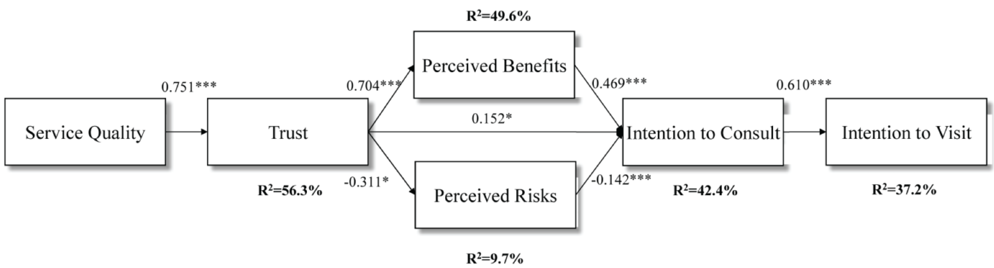
Structural Model

Figure 2 shows that service quality has a significant positive effect on trust (β=0.751, $p<0.001$). Thus, H1 is supported. Trust positively influences perceived benefits (β=0.704, $p<0.001$) and the intention to consult (β=0.152 $p<0.05$) and negatively influences perceived risks (β=-0.311, $p<0.05$), providing support for H2, H3, and H4. Perceived benefits positively influence the intention to consultant

Table 4. Variance inflation factor values

	TR	PB	PR	IC	IV
SQ	1.00				
TR		1.00	1.00	2.00	
PB				2.06	
PR				1.15	
IC					1.00

Figure 2. Results for the full sample



*p<0.05; **p<0.01; ***p<0.001

(β=0.469, p<0.001), while perceived risks negatively influence the intention to consult (β=-0.142, p<0.001). Thus, H5 and H6 are supported. The intention to consult has a significant positive effect on the intention to visit (β=0.610, p<0.001), supporting H7. The variance explained by trust, perceived benefits, perceived risks, the intention to consult, and the intention to visit are 56.3%, 49.6%, 9.7%, 42.4%, and 37.2%, respectively.

The respondents are classified into two types, i.e., free group and paid group. As shown in Table 5, the two groups have similar results regarding the hypothesized relationships. Service quality has a significant positive effect on trust. Trust positively influences perceived benefits and negatively influences perceived risks. Perceived benefits positively influence the intention to consult. The intention to consult positively influences the intention to visit. However, trust has no significant effect on the intention to consult for the free group, while perceived risks have no significant effect on the intention to consult for the paid group. Figures 3 and 4 show the analysis results for the two types.

Multi-Group Analysis

H8 was proposed to verify how payment types moderate the relationships between perceived benefits, perceived risks, trust, and the intention to consult, as well as the relationship between the intention to consult and the intention to visit. PLS-MGA was used to statistically verify the differences between free and paid groups. Before conducting PLS-MGA, the MICOM was suggested to conduct an analysis of the three procedures, including configural invariance, compositional invariance, and the equality of composite mean values and variances (Hair et al., 2019; Henseler et al., 2016).

First, free and paid groups have the same constructs, data treatment, and measurement and structural models, indicating configural invariance. Second, a permutation test was used to assess compositional invariance. If the c values exceed the 5% quantile, compositional invariance will be established between the two groups. Table 6 reveals that the c values for all constructs fall between the

Figure 3. Results for the free group

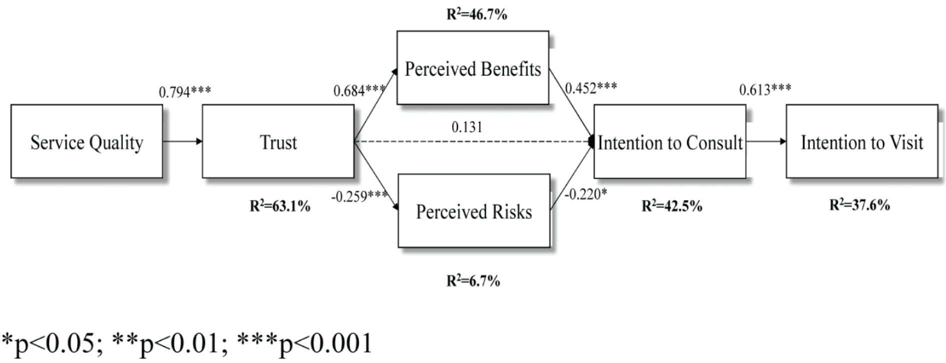


Figure 4. Results for the paid group

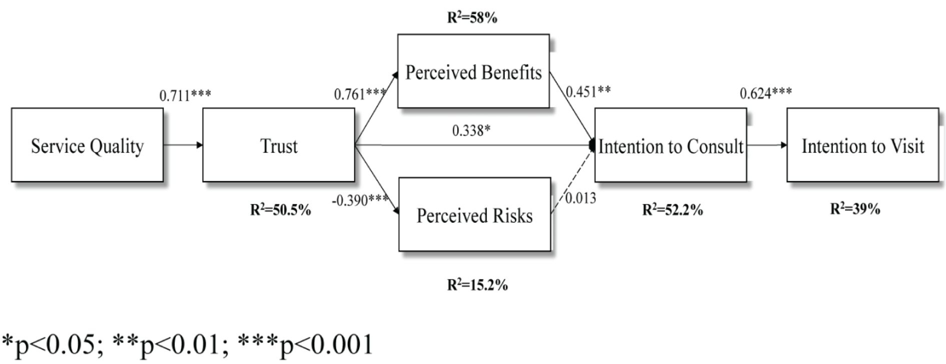


Table 5. Results of direct relationships

Hypothesis	Full sample		Free group		Paid group	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
H1: SQ→TR	0.751	0.000	0.794	0.000	0.711	0.000
H2: TR→PB	0.704	0.000	0.684	0.000	0.761	0.000
H3: TR→PR	-0.311	0.046	-0.259	0.001	-0.390	0.000
H4: TR→IC	0.152	0.044	0.131	0.169	0.338	0.013
H5: PB→IC	0.469	0.000	0.452	0.000	0.451	0.002
H6: PR→IC	-0.142	0.000	-0.220	0.028	0.013	0.859
H7: IC→IV	0.610	0.000	0.613	0.000	0.624	0.000

Table 6. Measurement invariance test using MICOM

Composite	c value (=1)	95% confidence interval	Compositional invariance
SQ	1.000	[0.993; 1.000]	Yes
TR	1.000	[0.999; 1.000]	Yes
PB	0.999	[0.999; 1.000]	Yes
PR	0.999	[0.998; 1.000]	Yes
IC	1.000	[1.000; 1.000]	Yes
IV	1.000	[0.999; 1.000]	Yes
Composite	**Difference of the composite's mean value (=0)**	**95% confidence interval**	**Equal mean values**
SQ	0.192	[-0.241; 0.237]	Yes
TR	0.310	[-0.263; 0.240]	No
PB	0.063	[-0.243; 0.270]	Yes
PR	0.040	[-0.245; 0.244]	Yes
IC	-0.202	[-0.253; 0.249]	Yes
IV	-0.017	[-0.277; 0.262]	Yes
Composite	**Difference of the composite's variance ratio (=0)**	**95% confidence interval**	**Equal variances**
SQ	-0.112	[-0.384; 0.382]	Yes
TR	-0.323	[-0.356; 0.398]	Yes
PB	0.296	[-0.554; 0.567]	Yes
PR	0.113	[-0.318; 0.320]	Yes
IC	0.765	[-0.610; 0.533]	No
IV	0.371	[-0.554; 0.488]	Yes

upper and lower bounds of the 95% confidence interval, indicating the establishment of compositional invariance. Third, except for trust and the intention to consult, the composites' mean values and variances for all constructs span between the upper and lower bounds of the 95% confidence interval. Thus, partial measurement invariance is established for the two groups.

After evaluating the measurement invariance, this study further used PLS-MGA to examine the significance level of the hypothesized relationships between the two groups. As shown in Table 7, the effect of perceived risks on the intention to consult is significantly larger for the free group (β=-0.220) than for the paid group (β= 0.013). However, there is no significant difference in the relationships

Table 7. Comparative results between free and paid groups

Hypothesis	Path coefficients-diff (| free – paid|)	p-value (free vs. paid)	Results
H8a: TR→IC	-0.207	0.187	Not support
H8b: PB→IC	0.001	0.993	Not support
H8c: PR→IC	-0.233	0.075*	Support
H8d: IC→IV	-0.012	0.927	Not support

*p<0.1; **p<0.05; ***p<0.01

between trust, perceived benefits, and the intention to consult, or in the relationship between the intention to consult and the intention to visit. Thus, the results partially support H8.

DISCUSSION

All hypotheses are supported by the full sample. The data are further divided into free and paid groups. Six of the seven hypothesized relationships are found to be significant for the free and paid groups. The effect of service quality on trust, the effect of trust on perceived benefits and perceived risks, the effect of perceived benefits on the intention to consult, and the effect of the intention to consult on the intention to visit are significant in both groups. The findings are consistent with those of many studies related to the extended valence framework (Lee et al., 2018; Lu et al., 2011; Ryu et al., 2018).

The direct path between trust and the intention to consult is significant for the paid group but not for the free group. The insignificant relationship between trust and behavioral intentions seems to contradict the findings of most studies (Lee et al., 2018; Li et al., 2018; Hong et al., 2019; Wan et al., 2020). The Good Doctor website (i.e., haodf.com) allows doctors to provide free or paid online consultation services. In the beginning, some doctors are willing to provide free services to attract more patients. After the patients were satisfied with their services, the doctors charged for each consultation. Generally, patients who have paid for online consultation services may have a higher level of trust in doctors than those who have not paid. Thus, the influence of trust is significant only for the paid group.

The relationship between perceived risks and the intention to consult is significant for the free group but not for the paid group. The insignificant relationship between risks and behavioral intentions is consistent with the findings of the existing research (Gong et al., 2019; Hong et al., 2019; Ozturk et al., 2017). One possible explanation is that the respondents are from the paid group, who has a strong perception of control regarding the online health consultation. Before accepting the payment mode, most patients will actively understand the doctors' professional capabilities based on the ratings and comments provided by other patients who have consulted the same doctors. Since patients can identify potential risks and avoid any risky behavior, they perceive a low risk of consulting online doctors, which in turn has no significant impact on their willingness to consult doctors.

The study demonstrates that the relationships between patients' perceptions and behavioral intentions vary with different payment types, which are in accordance with the findings of previous studies investigating the moderating effects of consumer characteristics (Arfi et al., 2021; Arfi et al., 2021; Chen et al.., 2020; Hong et al., 2019; Ryu, 2018). According to the MGA results, the effect of perceived risks on the intention to consult is stronger for the free group than for the paid group. This finding indicates that if the respondents are from the free group, their perceived risks are highly related to their intention to consult doctors. Compared with the paid group, the free group may not be familiar with online doctors, so they may be more sensitive to risks.

IMPLICATIONS FOR THEORY AND PRACTICE

Implications for Theory

This study makes some theoretical contributions. Previous studies have heavily focused on the adoption of eHealth services (Chang et al., 2016; Cho, 2016; Dünnebeil et al., 2012; Lai & Wang, 2015; Turan et al., 2015). However, little research has focused on investigating the relationship between online and offline channels in eHealth. This study develops a model to examine patients' decisions to use online and offline health services by integrating the extended valence framework and the halo effect. Since the proposed model accounts for 42.4% of the variance in the intention to consult and 37.2% of the variance in the intention to visit, our theoretical model contributes to the literature on eHealth.

This study enriches the eHealth literature by distinguishing between payment types (free and paid consultation). Our results indicate that the effects of trust and perceived risks on the intention to consult are different, depending on the payment types. The payment types moderate the relationship between trust and the intention to consult and between perceived risks and the intention to consult. The difference between free and paid groups is further empirically validated. Thus, the adoption of online health consultations does not depend on the characteristics of online health services but also on the characteristics of patients. Since the payment type is a significant research contribution, future research can consider the influence of other aspects on behavioral intentions, such as usage types (e.g., consultation by telephone or by texts), usage purpose (social use or process use), and disease types (chronic or non-chronic disease) (Song et al., 2021).

Drawing upon the extended valence framework, perceived benefits and perceived risks are crucial in determining patients' intentions to consult doctors. Trust is found to increase perceived benefits and decrease perceived risks. Thus, trust and privacy risks cannot be ignored when promoting eHealth use (Shiau et al., 2021). In addition, the results show that service quality plays a critical role in determining trust. We enrich the extended valence framework by incorporating service quality into the research model. The inclusion of service quality in the extended valence framework can improve our understanding of patients' decision-making patterns. Future research is encouraged to explore other external variables (e.g., doctor reputation, doctor title, and hospital brand) in eHealth.

This study introduces the halo effect to explain the relationship between online and offline channels in eHealth. We empirically test the effect of the intention to consult on the intention to visit. The results show that patients' intentions to visit doctors can be driven by their intentions to consult doctors. The findings provide valuable insights for understanding patients' decision-making processes from online to offline health services. In addition to online consultation services, future studies are suggested to explore how other online health services (e.g., online appointments, health information seeking, and patient-centered communication) influence patients' intentions to visit doctors.

Implications for Practice

During the outbreak of the COVID-19 pandemic, governments encouraged people to reduce unnecessary offline hospital visits. Thus, increasing patients' intentions to consult doctors becomes an important issue. In particular, eHealth not only helps doctors realize remote diagnosis and treatment but also helps patients save considerable time and offers convenience (Shiau et al., 2021). Thus, this study aims to increase patients' intentions to consult doctors through service quality, trust, and positive and negative valences. We provide valuable practical implications for online doctors and online health service providers.

Service quality has been found to be an important factor in eHealth as well as e-commerce contexts. The service quality provided by doctors exerts a strong influence on patients' trust in doctors. Thus, doctors are advised to improve the consultation quality, including the explanation of diseases and interaction with patients. In addition to improving doctors' service quality, the online health platform can provide a rating system and ranking of doctors to effectively manage the service quality. This information can also enhance patients' confidence in doctors and increase the number of online consultations.

Trust not only maximizes perceived benefits but also minimizes risk perceptions. Trust also plays a critical role in determining patients' intentions to consult doctors. To inspire higher levels of confidence in patients, doctors must not only have enough knowledge, skills and experiences to address online consultations but must also proactively work to sustain trust. Apart from improving trust in doctors, online health service providers can also build a trust mechanism and improve the reputation of the platform to enhance patient trust.

In terms of positive valence, perceived benefits are demonstrated to be an important antecedent of patients' intentions to consult online doctors. In the eHealth setting, patients aim to spend less money and time by consulting online doctors in a convenient manner. Thus, doctors should emphasize the benefits of online consultations, such as time and cost savings, and the ease of gaining a wider range of medical knowledge from doctors. Because online health consultation is a task-oriented service for patients, the utility that the patients expect to gain depends on the outcome of online consultations. Thus, doctors should be committed to meeting patients' needs and providing a satisfactory experience.

In terms of negative valence, the findings indicate the potential uncertainties involved in the collection, use, and disclosure of personal information as patient concerns. This study suggests that online doctors and online health service providers address privacy and ethical issues. Doctors should ensure patients that they never engage in opportunistic behavior. In addition, online health service providers should invest a considerable amount of time, effort and money to establish secure data transmission on the platform and make an effort to provide protection policies for personal information (i.e., medical consultations, medical treatments, and medicine prescriptions).

The original extended valence framework did not include payment types. Our results indicate that payment types result in different perceptions and behavioral intentions. The free group is concerned about privacy and security risks, while the paid group mainly focuses on trust in doctors. Thus, doctors should understand that the relationships between perceived risks and the intention to consult are different, depending on the payment types. We suggest that doctors develop different strategies to allocate health resources to the targeted groups. For example, doctors should try to minimize risk perceptions for the free group and increase trust for the paid group.

CONCLUSION

This study aims to investigate patients' decisions to use online and offline health services during the COVID-19 pandemic. More specifically, we propose and test a research model to examine the effects of positive valence (perceived benefits) and negative valence (perceived risks) on the intention to consult. Service quality is incorporated into the research model as the external variable of the extended valence framework. In addition, the moderating effects of payment types (free and paid consultation) on behavioral intentions are analyzed. To the best of our knowledge, this study is the first to investigate the moderating effects of payment types on patients' intentions to consult and visit doctors in eHealth.

The findings reveal that service quality is an antecedent of trust. Drawing on the extended valence framework, trust significantly influences perceived benefits and perceived risks, while trust, perceived benefits, and perceived risks significantly influence the intention to consult. By testing the halo effect in a multichannel setting, the intention to consult positively influences the intention to visit. Considering payment types, the influence of perceived risks on the intention to consult is larger for the free group than for the paid group. The findings are useful to understand patients' decisions to use online and offline health services for both researchers and practitioners.

LIMITATIONS AND FUTURE RESEARCH

This study has some limitations. First, this study explored whether patients with online consultation experiences go to hospitals for treatment. Our proposed model used behavioral intentions to investigate the willingness to visit doctors. Although behavioral intentions and actual behavior are closely related, future research can conduct longitudinal studies to investigate actual behavior to increase the research validity.

Second, the purpose of using eHealth services was restricted to a specific health service, that is, online health consultations. Different usage purposes may result in different perceptions and behaviors (Song et al., 2021). Further research is needed to consider other online health services to investigate users' purposes, including online appointments, health information seeking, and patient-centered communication.

Third, our data were collected from patients on a specific health platform (i.e., haodf.com). As online health platforms with different business models provide different functions, online health services, and payment modes, the generalizability of our results may be limited. Future research can collect data from other health platforms and compare the findings across different platforms.

Finally, this study examined a limited number of antecedents of behavioral intentions in eHealth. During the COVID-19 pandemic, pandemic fears change user behaviors toward information systems and/or information technology (Shiau et al., 2021). The effect of the COVID-19 pandemic plays a vital role in eHealth. Additionally, other variables that could lead to the intention to consult and visit doctors, including platform factors (e.g., interface and system quality) and hospital factors (e.g., hospital brand and location), can be considered in future research.

ACKNOWLEDGMENT

This research was funded by the Ministry of Science and Technology of Taiwan (MOST 109-2410-H-025-001-MY2, MOST 109-2314-B-227-009) and the National Natural Science Foundation of China (71572187).

REFERENCES

Arfi, W. B., Nasr, I. B., Khvatova, T., & Zaied, Y. B. (2021). Understanding acceptance of eHealthcare by IoT natives and IoT immigrants: An integrated model of UTAUT, perceived risk, and financial cost. *Technological Forecasting and Social Change*, *163*, 120437. Advance online publication. doi:10.1016/j.techfore.2020.120437

Arfi, W. B., Nasr, I. B., Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change*, *88*, 313–324. doi:10.1016/j.techfore.2013.10.005

Bedué, P., & Fritzsche, A. (2021). Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption. *Journal of Enterprise Information Management*, *363*. Advance online publication. doi:10.1136/bmj.m363

Chang, I. C., Chou, P. C., Yeh, R. K. J., & Tseng, H. T. (2016). Factors influencing Chinese tourists' intentions to use the Taiwan Medical Travel App. *Telematics and Informatics*, *33*(2), 401–409. doi:10.1016/j.tele.2015.09.007

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

Chang, Y. W., Hsu, P. Y., & Yang, Q. M. (2018). Integration of online and offline channels: a view of O2O commerce. *Internet Research, 28*(4), 926-945. 10.1108/IntR-01-2017-0023

Chen, J., Lan, Y. C., Chang, Y. W., & Chang, P. Y. (2020). Exploring doctors' willingness to provide online counseling services: The roles of motivations and costs. *International Journal of Environmental Research and Public Health*, *17*(1), 110. doi:10.3390/ijerph17010110 PMID:31877861

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295-336. 10.1108/S1745-3542(2012)0000008007

Cho, J. (2016). The impact of post-adoption beliefs on the continued use of health apps. *International Journal of Medical Informatics*, *87*, 75–83. doi:10.1016/j.ijmedinf.2015.12.016 PMID:26806714

Cowan, M. L., & Little, A. C. (2013). The effects of relationship context and modality on ratings of funniness. *Personality and Individual Differences*, *54*(4), 496–500. doi:10.1016/j.paid.2012.10.020

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9–30. doi:10.1080/07421222.2003.11045748

Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e–commerce transactions. *Information Systems Research*, *17*(1), 61–80. doi:10.1287/isre.1060.0080

Dunham, A. H., & Burt, C. D. B. (2011). Organizational memory and empowerment. *Journal of Knowledge Management*, *15*(15), 851–868. doi:10.1108/13673271111174366

Dünnebeil, S., Sunyaev, A., Blohm, I., Leimeister, J. M., & Krcmar, H. (2012). Determinants of physicians' technology acceptance for e-health in ambulatory care. *International Journal of Medical Informatics*, *81*(11), 746–760. doi:10.1016/j.ijmedinf.2012.02.002 PMID:22397989

Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information Systems*, *16*(1), 91–109. doi:10.17705/1CAIS.01605

Gefen, D., Straub, D. W., & Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, *4*(7), 1–70. doi:10.17705/1CAIS.00407

Gong, Z., Han, Z., Li, X., Yu, C., & Reinhardt, J. D. (2019). Factors Influencing the Adoption of Online Health Consultation Services: The Role of Subjective Norm, Trust, Perceived Benefit, and Offline Habit. *Frontiers in Public Health*, *7*, 286–286. doi:10.3389/fpubh.2019.00286 PMID:31637229

Hair, J. F. (2009). Multivariate data analysis. *Journal of Multivariate Analysis*, *1*(3), 316–346. doi:10.1016/0047-259X(71)90006-6

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. doi:10.1108/EBR-11-2018-0203

Hamida, S. T. B., Ahmed, B., Cvetkovic, D., Jovanov, E., Kennedy, G., & Penzel, T. (2015). A new era in sleep monitoring: the application of mobile technologies in insomnia diagnosis. In S. Adibi (Ed.), *Mobile Health: A Technology Road Map* (pp. 101–127). Springer Science and Business Media LLC. doi:10.1007/978-3-319-12817-7_5

Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International Marketing Review*, *33*(3), 405–431. doi:10.1108/IMR-09-2014-0304

Hong, Y., Wan, M., & Li, Z. (2021). Understanding the health information sharing behavior of social media users: An empirical study on WeChat. *Journal of Organizational and End User Computing*, *33*(5), 180–203. doi:10.4018/JOEUC.20210901.oa9

Hong, Z., Deng, Z., & Zhang, W. (2019). Examining factors affecting patients trust in online healthcare services in China: The moderating role of the purpose of use. *Health Informatics Journal*, *25*(4), 1647–1660. doi:10.1177/1460458218796660 PMID:30192694

Huang, L. C., & Shiau, W. L. (2017). Factors affecting creativity in information system development: Insights from a decomposition and PLS-MGA. *Industrial Management & Data Systems*, *117*(3), 496–520. doi:10.1108/IMDS-08-2015-0335

Jarvenpaa, S. L., Tractinsky, N., & Vitale, M. (2000). Consumer trust in an internet store. *Information Technology and Management*, *5*(2), 45–71. doi:10.1023/A:1019104520776

Jin, B., Park, J. Y., & Kim, J. (2010). Joint influence of online store attributes and offline operations on performance of multichannel retailers. *Behaviour & Information Technology*, *29*(1), 85–96. doi:10.1080/01449290701497202

Khan, G.F., Sarstedt, M., Shiau, W.L., Hair, J.F., Ringle, C.M. & Fritze, M.P. (2019). Methodological research on partial least squares structural equation modeling (PLS-SEM). *Internet Research, 29*(3), 407-429. 10.1108/IntR-12-2017-0509

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2009). Trust and satisfaction, two stepping stones for successful e-commerce relationships: A longitudinal exploration. *Information Systems Research*, *20*(2), 237–257. doi:10.1287/isre.1080.0188

Kwon, W. S., & Lennon, S. J. (2009). What induces online loyalty? Online versus offline brand images. *Journal of Business Research*, *62*(5), 557–564. doi:10.1016/j.jbusres.2008.06.015

Lai, J. Y., & Wang, J. (2015). Switching attitudes of Taiwanese middle-aged and elderly patients toward cloud healthcare services: An exploratory study. *Technological Forecasting and Social Change*, *100*(92), 155–167. doi:10.1016/j.techfore.2014.06.004

Le, W., Chang, P. Y., Chang, Y. W., & Chen, J. (2019). Why do patients move from online health platforms to hospitals? The perspectives of fairness theory and brand extension theory. *International Journal of Environmental Research and Public Health*, *16*(19), 3755–3755. doi:10.3390/ijerph16193755 PMID:31590419

LeadLeo. (2020) *eHealth Market Size to Reach USD 230640.4 Million By 2027 at a CAGR Of 14.5% - Valuates Reports*. https://www.prnewswire.com/news-releases/ehealth-market-size-to-reach-usd-230640-4-million-by-2027-at-a-cagr-of-14-5---valuates-reports-301250183.html

Lee, M. C. (2009). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications*, *8*(3), 130–141. doi:10.1016/j.elerap.2008.11.006

Lee, Z. W., Chan, T. K., Balaji, M. S., & Chong, A. Y. L. (2018). Why people participate in the sharing economy: an empirical investigation of Uber. *Internet Research, 28*(3), 829-850. 10.1108/IntR-01-2017-0037

Li, D., Hu, Y., Pfaff, H., Wang, L., Deng, L., Lu, C., Xia, S., Cheng, S., Zhu, X., & Wu, X. (2020). Determinants of patients' intention to use the online inquiry services provided by internet hospitals: Empirical evidence from China. *Journal of Medical Internet Research*, *22*(10), e22716. doi:10.2196/22716 PMID:33006941

Li, J., Liu, M., Liu, X., & Ma, L. (2018). Why and when do patients use e-consultation services? The trust and resource supplementary perspectives. *Telemedicine Journal and e-Health*, *24*(1), 77–85. doi:10.1089/tmj.2016.0268 PMID:28686084

Li, Y., & Wang, X. (2018). Seeking health information on social media: A perspective of trust, self-determination, and social support. *Journal of Organizational and End User Computing*, *30*(1), 1–22. doi:10.4018/JOEUC.2018010101

Lu, Y., Cao, Y., Wang, B., & Yang, S. (2011). A study on factors that affect users' behavioral intention to transfer usage from the offline to the online channel. *Computers in Human Behavior*, *27*(1), 355–364. doi:10.1016/j.chb.2010.08.013

Marketsandmarkets.com. (2018). *Global Forecast to 2023*. https://www.marketsandmarkets.com/Market-Reports/eHealth-market-11513143.html

Mathieson, K., Peacock, E., & Chin, W. W. (2001). Extending the technology acceptance model: the influence of perceived user resources. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 32*(3), 86-112. 10.1145/506724.506730

Mou, J., Cohen, J., Dou, Y., & Zhang, B. (2019). International buyers' repurchase intentions in a Chinese cross-border e-commerce platform: A valence framework perspective. *Internet Research, 30*(2), 403-437. 10.1108/INTR-06-2018-0259

Ozturk, A. B., Bilgihan, A., Salehi-Esfahani, S., & Hua, N. (2017). Understanding the mobile payment technology acceptance based on valence theory. *International Journal of Contemporary Hospitality Management*, *29*(8), 2027–2049. doi:10.1108/IJCHM-04-2016-0192

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, *7*(3), 101–134. doi:10.1080/10864415.2003.11044275

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

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531–544. doi:10.1177/014920638601200408

Ren, C., Deng, Z., Hong, Z., & Zhang, W. (2019). Health information in the digital age: An empirical study of the perceived benefits and costs of seeking and using health information from online sources. *Health Information and Libraries Journal*, *36*(2), 153–167. doi:10.1111/hir.12250 PMID:30737878

Ryu, H. S. (2018). What makes users willing or hesitant to use Fintech?: The moderating effect of user type. *Industrial Management & Data Systems*, *118*(3), 541–569. doi:10.1108/IMDS-07-2017-0325

Shiau, W. L., & Chau, P. Y. (2016). Understanding behavioral intention to use a cloud computing classroom: A multiple model comparison approach. *Information & Management*, *53*(3), 355–365. doi:10.1016/j.im.2015.10.004

Shiau, W. L., Siau, K., Yu, Y., & Guo, J. (2021). Research commentary on IS/IT role in emergency and pandemic management: Current and future research. *Journal of Database Management*, *32*(2), 67–75. doi:10.4018/JDM.2021040105

Shiau, W. L., Yuan, Y., Pu, X., Ray, S., & Chen, C. C. (2020). Understanding Fintech continuance: Perspectives from self-efficacy and ECT-IS theories. *Industrial Management & Data Systems*, *120*(9), 1659–1689. doi:10.1108/IMDS-02-2020-0069

Song, X., Song, S., Zhao, Y., & Min, H. (2021). Fear of missing out (FOMO) toward ICT use during public health emergencies-An investigation on predictors and outcomes. *Journal of Database Management*, *32*(2), 20–35. doi:10.4018/JDM.2021040102

Thorndike, E. L. (1920). A constant error in psychological ratings. *The Journal of Applied Psychology*, *4*(1), 25–29. doi:10.1037/h0071663

Turan, N., Kaya, N., & Aydın, G. Ö. (2015). Health problems and help seeking behavior at the internet. *Procedia: Social and Behavioral Sciences*, *195*, 1679–1682. doi:10.1016/j.sbspro.2015.06.248

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *Management Information Systems Quarterly*, *27*(3), 425–478. doi:10.2307/30036540

Wan, Y., Zhang, Y., & Yan, M. (2020). What influences patients' willingness to choose in online health consultation? An empirical study with PLS–SEM. *Industrial Management & Data Systems*, *120*(12), 2423–2446. doi:10.1108/IMDS-11-2019-0633

Wimmer, H., & Yoon, V. Y. (2017). Counterfeit product detection: Bridging the gap between design science and behavioral science in information systems research. *Decision Support Systems*, *104*, 1–12. doi:10.1016/j.dss.2017.09.005

Xing, W., Hsu, P. Y., Chang, Y. W., & Shiau, W. L. (2019). How does online doctor–patient interaction affect online consultation and offline medical treatment? *Industrial Management & Data Systems*, *120*(1), 196–214. doi:10.1108/IMDS-05-2019-0261

Yang, S., Lu, Y., Zhao, L., & Gupta, S. (2011). Empirical investigation of customers' channel extension behavior: Perceptions shift toward the online channel. *Computers in Human Behavior*, *27*(5), 1688–1696. doi:10.1016/j.chb.2011.02.007

Zhang, Y., Kong, F., Zhong, Y., & Kou, H. (2014). Personality manipulations: Do they modulate facial attractiveness ratings? *Personality and Individual Differences*, *70*(11), 80–84. doi:10.1016/j.paid.2014.06.033

Zhou, T. (2013). An empirical examination of user adoption of location–based services. *Electronic Commerce Research*, *13*(1), 25–39. doi:10.1007/s10660-013-9106-3

Zhou, T. (2014). Understanding the determinants of mobile payment continuance usage. *Industrial Management & Data Systems*, *114*(6), 936–948. doi:10.1108/IMDS-02-2014-0068

Zhou, T., Li, H., & Liu, Y. (2010). The effect of flow experience on mobile SNS users' loyalty. *Industrial Management & Data Systems*, *110*(6), 930–946. doi:10.1108/02635571011055126

APPENDIX

Table 8. Definition and measurements of constructs

Construct	Measurement items	Sources
Service Quality	**The overall assessment of the service performance associated with online consultation services.** SQ1: This doctor provides assured services. SQ2: This doctor provides services with empathy. SQ3: This doctor provides responsive services.	DeLone and McLean (2003)
Trust	**The expectation about the motives and behaviors of online doctors.** TR1: This doctor' is trustworthy. TR2: This doctor wants to be known as one who keeps promises and commitments. TR3: I trust this doctor keeps my best interests in mind.	Jarvenpaa et al. (2000)
Perceived Benefits	**The perception of the utility associated with online consultation services.** PB1: I think that consulting the doctor can save my time. PB2: I think that consulting the doctor online can offer me a wider range of medical knowledge. PB3: I think that consulting the doctor can save the costs.	Lee (2009)
Perceived Risks	**The perception of privacy and security risk concerns associated with online consultation services.** What do you believe is the risk for the doctor's consultation due to the possibility that: PR1: Personal information submitted could be misused? PR2: Personal information could be made available to unknown individuals or companies without your knowledge? PR3: Personal information could be made available to hospital institutions?	Dinev & Hart (2006)
Intention to Consult	**The strength of the willingness to consult doctors.** IC1: I intend to consult this doctor. IC2: I predict I would consult this doctor. IC3: I plan to consult this doctor.	Venkatesh et al. (2003)
Intention to Visit	**The strength of the willingness to visit doctors in the hospital.** IV1: I intend to visit this doctor in the hospital in the future. IV2: I predict I would visit this doctor in the hospital in the future. IV3: I plan to visit this doctor in the hospital in the future.	Venkatesh et al. (2003)

Table 9. Profile of respondents

Measure	Items	Free	Paid	Summary	
Gender	Male	67	56	123	(55.7%)
	Female	48	50	98	(44.3%)
Age	18-25 years	19	8	27	(12.2%)
	26-35 years	55	63	118	(53.4%)
	36-45 years	29	23	52	(23.5%)
	46-55 years	9	10	19	(8.6%)
	56-65 years	2	2	4	(1.8%)
	Over 65 years	1		1	(0.5%)
Education	Senior high school	32	28	60	(27.1%)
	University	73	72	145	(65.6%)
	Master	10	6	16	(7.2%)
Monthly Income	Less than 1500 yuan	15	11	26	(11.8%)
	1501-3000 yuan	21	19	40	(18.1%)
	3001-4500 yuan	20	20	40	(18.1%)
	4501-6000 yuan	23	21	44	(19.9%)
	6001-7500 yuan	10	10	20	(9.0%)
	7501-9000 yuan	7	10	17	(7.7%)
	9001-10500 yuan	7	7	14	(6.3%)
	More than 10500 yuan	12	8	20	(9.0%)
Online Consultation Experience	Less than 1 year	58	51	109	(49.3%)
	1 year	28	30	58	(26.2%)
	2 years	13	14	27	(12.2%)
	3 years	5	6	11	(5.0%)
	4 years	2	2	4	(1.8%)
	5 years	3	0	3	(1.4%)
	More than 5 years	6	3	9	(4.1%)
Online Consultation Frequency (Monthly)	1 time	29	22	51	(23.1%)
	2 times	26	25	51	(23.1%)
	3 times	25	21	46	(20.8%)
	4 times	21	23	44	(19.9%)
	5 times	6	8	14	(6.3%)
	More than 5 times	8	7	15	(6.8%

Suli Zheng is a Professor and Associate Dean at School of Economics and Management, China Jiliang University, China. She received her Ph.D from Zhejiang University. Her research interests include innovation management, knowledge management and e-commerce. Her papers have been published in Management Decision, Journal of Knowledge Management, and International Journal of Strategic Management.

Po-Ya Chang is an Assistant Professor in Department of Leisure Industry and Health Promotion, National Taipei University of Nursing and Health Sciences, since 2019. She received her Ph.D. degree from College of Public Health of Taipei Medical University in 2016. Her research areas include public health, epidemiology, preventive medicine, and big data analysis. Her research topic focuses on diabetes patient managements and kidney disease prevent strategies. She has published 19 academic papers in international journals and at international conferences.

Jiahe Chen is currently a Ph.D. candidate in the School of Business, Western Sydney University. He received the MSc in Information Technology Management (Distinction) from the Department of Computer Science, Hong Kong Baptist University. In 2015, he was awarded double bachelor's degrees in Management and Economics. His current research interest covers electronic/mobile commerce, eHealth, e-business, and smart retailing. He also published more than 10 journal and conference articles, such as Journal of Retailing and Consumer Services, Data Technologies and Applications, International Journal of Environmental Research and Public Health, among others.

Yu-Wei Chang, Corresponding Author, is an Assistant Professor in the Department of Business Management and the Director of Intelligence Academia-Industry Research Center of National Taichung University of Science and Technology. He got Ph.D. degree from the Department of Business Administration of National Central University. He also serves an e-business consultant to provide counseling services for SMEs. His research areas are e-commerce, tourism management, business intelligence, enterprise resource planning, and knowledge management. He has published more than 40 journal and conference articles. Yu-Wei Chang can be contacted at: nickychang@nutc.edu.tw.

Hueng-Chuen Fan, Corresponding Author, is a senior consultant in the department of Pediatrics, specialized in the Pediatric Neurology and a head of the department of Medical research, Tungs' Taichung Metroharbor Hospital, Taiwan. He holds a PhD. Degree in the department of Pharmacology, University of Cambridge, UK. He also positions as an Associated Professor in the department of Life Sciences, National Chung Hsing University, Taichung and the department of Nursing and Management, Jen-Teh Junior College of Medicine, Miaoli, Taiwan. His research areas are versatile, mainly in ion channels, neuroscience, and respiratory medicine. He has published more than 70 SCI articles and 6 medical text books in Chinese. Hueng-Chuen Fan can be contacted at: t11578@ms.sltung.com.tw.