THE IMPACT OF PRIVACY CALCULUS AND TRUST ON USER INFORMATION PARTICIPATION BEHAVIOR IN AI-BASED MEDICAL CONSULTATION-THE MODERATING ROLE OF GENDER

Yumei Luo
School of Business and Tourism Management
Yunnan University, China
luoyumei@ynu.edu.cn

Xiaoqi Li
School of Business and Tourism Management
Yunnan University, China
1291045447@qq.com

Qiongwei Ye*
Business School
Yunnan University of Finance and Economics, China
yeqiongwei@163.com

ABSTRACT

Artificial intelligence (AI)-based medical consultation, an emerging health service delivered on digital platforms, has been widely applied on major medical platforms. How to encourage users' information participation is a key issue for AI-based medical consultation platforms to succeed. A research framework is developed which applies the privacy calculus theory and trust and includes gender differences to the prediction of information participation behavior in the medical consultation context. The suggested hypotheses are confirmed using a structural equation modeling approach and a multi-group investigation employing empirical data from 470 users. The empirical results indicate that there are significant positive relationships between perceived information control and perceived benefits, between perceived benefits and trust, and between trust and information participation behavior, while negative relationships are found between perceived information control and perceived risks, between perceived risks and perceived benefits/trust. Further, the relationships between privacy calculus and trust are contingent on gender. Specifically, females are more sensitive to perceived risks, whereas males pay more attention to perceived benefits. Theoretical, practical implications and limitations are also discussed.

Keywords: AI-based medical consultation; Privacy calculus; Information participation; Trust; Gender

1. Introduction

With the rapid development of artificial intelligence (AI), AI-based service provides unprecedented opportunities to improve service quality and customer interactions in various settings, such as hospitality and tourism (Li et al., 2021), public service delivery (Chen et al., 2021), ridesharing (Cheng et al., 2021), e-commerce (Adam et al., 2021) , and medical and healthcare (Kang et al., 2023). In the medical and healthcare setting, AI-based medical consultation, an emerging health self-service delivered on digital platforms where AI independently completes online consultation, answers questions and uses databases for case analysis, etc., is widely applied, such as eye diseases (Ćirković, 2020), leprosies (DeSouza et al., 2021), and general symptoms (Meyer et al., 2020; Miller et al., 2020). During the COVID-19 pandemic, around 15% of patients in China used online medical consultation platforms for healthcare information seeking, diagnosis, and treatment (Liu et al., 2020). Meyer et al. (2020) found that 91% of U.S. users were willing to accept AI-assisted symptom assessor (e.g., Isabel Symptom Checker). AI-based medical consultation apps (e.g., Ada, K Health, and HealthTap) have been downloaded from the Google Play Store more than one million times since the release (You and Gui, 2020).

* Corresponding author

A significant issue facing AI-based medical consultation platforms is how to encourage users to provide personal health-related information, that is, information participation behavior. Information participation behavior refers to the degree of information interaction with the platform, including providing, posting and giving responses to the platform (Kamboj and Rahman, 2017). The provision and collection of personal information will inevitably increase users' concerns about privacy loss (Guo et al., 2016), especially in the medical consultation context, personal health information is particularly prominent. For example, personal health information can be used for marketing purposes without authorization. Granting employers and insurance companies access to health information can lead to discrimination. Disclosure of sensitive health information (e.g., genetics, domestic violence, substance abuse, mental health, and sexually transmitted disease) can lead to social stigma. Health information privacy concerns arise when individuals are required to provide sufficient personal health information to obtain the benefits of utilizing AI-based medical consultation. These concerns can even cause individuals to refuse to provide information to AI-based medical consultation platforms and decline healthcare services from AI-based medical consultation platforms. Therefore, it is becoming increasingly important to investigate the underlying drivers of AI-based medical consultation users' information participation behaviors and privacy concerns. Despite the high service efficiency of AI technology in service industries (Duan et al., 2019), many users remain hesitant to embrace AI technology because they are concerned about the loss of privacy (Liu and Tao, 2022) and trust human judgment more than AI algorithms (Longoni et al., 2019).

Privacy calculus theory has been widely used by prior studies to understand individuals' information participation behavior in different contexts, including social networking sites (Min and Kim, 2015; Sun et al., 2021), sharing economy platforms (Cheng et al., 2021), and location-based services (Xu et al., 2009; Yun et al., 2013). It contends that individuals deal with the tradeoff between perceived benefits and perceived risks before disclosing personal information (Xu et al., 2009). In the AI-based medical consultation context, the information privacy dilemma has its uniqueness. On the one hand, health information disclosed in medical consultation is more sensitive than other forms of information (e.g., demographic profiles, purchase history information). Considerable sensitive information can increase the perceived risks and lower the intentions to disclose (Phelps et al., 2000). On the other hand, AI technologies have powerful automated ability to collect, analyze, and track personal information. For example, they can collect information from text, voice, tone, image, and etc. Such automated information collection may undermine individuals' privacy perception and participative behavior (Cheng et al., 2021). Individuals benefit from participating in AI-based medical consultation by obtaining health support rather than monetary rewards or enjoyment. Thus, a further examination of benefit-risk calculus and their relationships with information participation in the AI-based medical consultation context is required. In addition, as perceived information control allows users to govern how their personal information is gathered and handled and plays an important role in the process of privacy calculus (Cheng et al., 2021), we also consider perceived information control to investigate further its effects on the calculus of these net benefits.

Trust in AI-based medical consultation platforms may be a key factor in relation to privacy calculus and information participation behavior. Trust as a central mechanism is beneficial for explaining the relationship between individuals' beliefs and behavior (Lee and See, 2004). Sarkar et al. (2020) found that both perceived usefulness and ease of use were significant antecedents of trust, whereas user satisfaction and behavioral intention were consequences of trust. In the study of doctor-patient relationship, trust is considered an important factor affecting the doctor-patient relationship (Koirala, 2020; Lan and Yan, 2017). In addition, previous literature has indicated that the importance of trust becomes more apparent because humans have increasingly relied on technology (Ejdys, 2018). Trust in AI context involves trusting the intentions of AI and its processes (Ameen et al., 2021), which is highly uncertain since it is expected to learn, understand, adapt, and evolve (Kaplan and Haenlein, 2019). Trust is formed and modified within the medical consultation context and influenced by users' benefit-risk calculus, which then influences user's information participation. Thus, integrating trust with the privacy calculus to explain individuals' information participation is essential to obtain a more comprehensive insight into information participation in AI-based medical consultation.

Additionally, besides understanding the privacy calculus and trust during the information participation in the context of AI-based medical consultation, we are also interested in the individual differences in this process. While individual differences may come from many aspects, such as demographics and prior usage experiences (Bostrom et al., 1990), this study focuses on gender differences for three reasons. First, gender difference is one of the most fundamental differences among individuals, as male and female have different decision-making processes (Lin and Wang, 2020). Males and females play different social roles affecting their social behavior due to different societal and cultural expectations (Archer, 1996). Different social roles are likely to lead to behavioral differences between genders in various environments such as SNSs (Lin and Wang, 2020), smartphone security behavior (Ameen et al., 2019), and location-based services (Y. Li et al., 2021). Second, in the field of privacy concern and behavior, the finding of gender differences is mixed, with several studies reporting stronger privacy concerns in female (e.g., Shepherd, 2016; Thelwall and Vis, 2017), some studies showing no gender difference (Tufekci, 2007), and others showing stronger male privacy concerns (e.g., Dhir et al., 2016; Huang et al., 2018) . Thus, gender differences in the AI-based medical consultation context warrant further examination. Third, understanding gender differences is also of practical significance because gender information is easily identifiable and accessible in such a way that practitioners can effectively manage gender segments using different marketing strategies.

In summary, the current study's objective is to examine the role of trust in affecting individuals' information participation behavior by mediating the effects of privacy-related antecedent in the AI-based medical consultation context. Hence, we focus on the following three research questions: (1) how do perceived information control, benefits, and risks influence users' trust? (2) does trust influence information participation behavior? and (3) do these relationships in questions 1 and 2 vary across genders? To answer our research questions, a quantitative study including structural equation modeling (PLS-SEM) and multi-group analysis was conducted.

The rest of this paper is organized as follows. In the next section, we will review related literature about privacy calculus theory, trust and gender, and present the research model and hypotheses. Following that, the research methodology, sample, and data collection are explained in Section 3, which is followed by the data analysis and results in Section 4. Conclusion, theoretical and practical implications, and limitations and future research are shown in Section 5.

2. Literature Review and Research Hypotheses

2.1 Privacy Calculus Theory

Privacy is considered increasingly important for individuals, yet they can disclose certain degrees of personal information in specific contexts. For example, a user discloses her/his location information to gain social benefits and receive real-time rewards, such as traffic information, finding friends, obtaining discount coupons, or playing location-related games (Koohikamali et al., 2015; Xu et al., 2011). Similarly, to acquire timely and accurate assessment from the doctor during medical consultation, patients are willing to provide sufficient information regarding their health condition and past medical history (Jiang et al., 2021).

Privacy calculus theory explains how individuals deal with the tradeoff between perceived benefits and risks before disclosing personal information (Xu et al., 2009). Privacy calculus theory evolved from behavioral calculus proposed by Laufer and Wolfe (1977), who believed that the intention to disclose personal information was based on rational risk-benefit calculation. This model assumed that individuals could have a strong awareness of the costs and benefits of information disclosure at the same time, and the loss of privacy in information disclosure was acceptable when certain benefits were ensured and the risks were moderate. Hew et al. (2016) found that although users showed concern for privacy, they did not stop using such services continuously, which means there is a gap between users' privacy attitudes and their privacy behaviors, which is known as the "privacy paradox" phenomenon (Dinev and Hart, 2006). Some scholars have applied privacy calculus theory to explore the phenomenon of privacy paradox in social networks (Dienlin and Metzger, 2016), mobile applications (Wang et al., 2016) and e-commerce (Zhu et al., 2017). Culnan and Armstrong (1999) found that when users considered whether to provide personal information to service providers, they would weigh the advantages and disadvantages of privacy disclosure. When users felt that the benefits of privacy disclosure outweighed the risks, privacy paradox would occur. Dienlin and Trepte (2015) regarded user's privacy attitude as the main influencing factor of privacy paradox behavior. Kokolakis (2017) reviewed the research literature on privacy paradox and used different research results to confirm and explain the existence of privacy paradox with different backgrounds and different concepts. In the field of healthcare, Zhu et al. (2021) pointed out that in the mobile health scenario, perceived income had a greater impact on disclosure intention than privacy concerns. Furlong (1998) found that patients who previously did not provide clinical data changed their attitudes after seeing authoritative explanations, suggesting that authoritative explanations and trust can improve patients' willingness to disclose privacy. Lee and Kwon (2015) studied the influence of mobile health medical users' personal characteristics on the privacy paradox.

Specifically, individuals behave as though performing a risk-benefit analysis in assessing the outcomes they will receive from providing personal information to healthcare service providers. Perceived benefits refer to the perception of value derived from information disclosure, including direct and tangible benefits (e.g., saving cost and time) and intangible benefits that are difficult to measure (e.g., obtaining personalized services) (Alam et al., 2020). In this study, perceived benefits mainly refer to obtaining convenient services and accurate diagnosis by providing personal health information to the AI-based medical consultation platform. Perceived risk refers to the potential loss or danger from releasing personal information (Lee et al., 2014). For example, the disclosure of personal information may lead to financial or personal security risks (Chiu et al., 2014). We focus on the privacy risks, that is, potential loss of control over personal information (Featherman and Pavlou, 2003). It mainly shows that personal health information is accessed and used without users' permission or knowledge when using the AI-based medical consultation platform. From a specific context, individuals usually weigh both costs and benefits before deciding to disclose information (Dinev and Hart, 2005). Applying the privacy calculus theory to AI-based medical consultation suggests that users can rationally evaluate the perceived benefits and risks before deciding whether they will provide their health-related information.

Perceived information control plays an important role in privacy calculus. In the context of psychology, it refers to an individual's perception of the ability to control how personal information is collected, released, and disseminated (Xu et al., 2011). Informational control includes information gathering and handling controls, respectively (Alge et al., 2006). Specific to the AI-based medical consultation platform, perceived information control is defined as the extent to which an individual feels that AI-based medical consultation platform allows that individual to control the use of information through privacy settings in this study. Perceptual information control is an effective mechanism for enhancing positive feelings and reducing negative feelings (Cheng et al., 2021).

Studies have found that the higher the user's perception of information control, the more transparency there is in user data collection and use (Xu et al., 2011). On a consultation platform, when individuals feel that they can control their personal information, they are less concerned about the collection of their data and show a more positive attitude toward the disclosure of personal information (Hajli and Lin, 2016). Princi and Krämer (2020) found that perceived control of private data led to a higher perception of benefits. Especially in healthcare, this emphasizes the necessity of interventions (Princi and Krämer, 2020). With a high level of information control, individuals have lower perceived uncertainty (Lee et al., 2013). According to prior research, lower uncertainty surrounding context induces social attraction (Antheunis et al., 2010). It is highly probable that users feel more advantageous by sharing information with socially attractive people and expect a higher probability of feedback by sharing their health information. Thus, we hypothesize that:

H1: *Perceived information control has a significant positive effect on perceived benefits of information participation.*

Similarly, perceived information control reduces the perceived risks of disclosing individual health-related information, encouraging users to disclose their information. Perceived information control could effectively reduce privacy concerns (Xu et al., 2012), perceived uncertainty, and privacy invasion (Cheng et al., 2021), thereby positively affecting users' behavior at work (Alge et al., 2006). To reduce perceived risks, individuals adjust access visibility settings, friend settings, etc., to control what information is disclosed and shared and with whom (Belli et al., 2017). We hypothesize the following:

H2: *Perceived information control has a significant negative effect on perceived risks of information participation.*

Previous studies have shown that personalized information and services have serious privacy risks and affect users' perception of benefits (Kobsa, 2007). Due to risk aversion, the higher the perceived risk, the lower the user's attention and sensitivity to benefits (Chiu et al., 2014). In healthcare platforms, improper handling of user data and other personal health-related information can lead to loss of privacy. From the privacy calculus theory and when dealing with privacy issues, individuals perform a risk-benefit analysis of all factors related to a particular information disclosure situation to assess privacy concerns (Xu et al., 2011). Therefore, high perceived risk reduces perceived benefits. Generally, we can reasonably expect that the net benefit of users using intelligent consulting platforms is generated by the perceived benefit minus the perceived risk. From these conclusions, this paper proposes hypothesis:

H3: *Perceived risks of information participation have a significant negative effect on perceived benefits of information participation.*

2.2 Mediation Role of Trust

Trust plays a crucial role in promoting consumers' willingness to use, and this conclusion has been verified in management (Mayer et al., 1995), marketing (Morgan and Hunt, 1994), information systems (Hong et al., 2008), and online transactions (Hong and Ilyoo, 2015; Lee et al., 2021). Trust refers to the willingness of a party to be vulnerable to the actions of another party by expecting that the other party performs a particular action important to the trustor, irrespective of monitoring or control (Mayer et al., 1995). Morgan and Hunt (1994) pointed out that trust was an important factor in developing high-quality relationships.

In healthcare service, previous studies have highlighted the link between cognitive and emotional trust and individual behavior. Trust has been identified as the key to predicting user intentions to adopt and use behavior. Guo et al. (2016) pointed out that trust reduced individuals' privacy concerns and increased their willingness to adopt a platform. Zhao et al. (2018) stated that trust significantly impacted users' behavioral intentions toward mobile health services. Fox and Connolly (2018) found that trust alleviated elderly users' concerns about information privacy and increased their willingness to adopt m-Health. Akter et al. (2011) examined the impact of trustworthiness on continuance intention in m-Health information services.

Existing literature shows that trust is particularly important in the early stages of the human-AI relationship (Gursoy et al., 2019) and has been widely discussed in human-computer interaction (Hwang, 2009; Lee and See, 2004). In AI-based medical consultation, trust is seen as having confidence in an intelligent consultation platform. In this research context, trust in the AI-based medical consultation platform refers to the users' perceptions that the platforms of medical consultation are trustworthy and will not misuse their data.

2.2.1 Antecedents of Trust

With greater benefits of using AI-based medical consultation, users may trust the platform and give a better representation of their needs. Previous studies have also examined the linkage between perceived benefits and trust (Park et al., 2019). Moreover, Guo et al. (2016) pointed out that if a company were to provide more benefits, consumers would have an impression of a capable company, which would then increase their trust in it. Similarly, we argue that perceived benefits of AI services influence the way the medical consultation platform is trusted. If there are more perceived benefits from using AI-based consultation service, then it is more likely that the satisfied user will trust the medical consultation platform to deliver good privacy protection services. Based on the abovementioned arguments, we propose:

H4: *Perceived benefit of information participation has a significant positive effect on trust in AI-based medical consultation.*

When users perceive physical, psychological, privacy, functional, social, and financial risks in AI-based medical consultation, they choose to distrust the platform and its services to avoid losses and protect their interests, which is an instinct of users. This means that perceived risk negatively influences perceived trust (Yang et al., 2015). Risks concerning privacy, security, product price, and customer service are trust-related factors, the less of which will promote more trust in e-shopping (Kim and Benbasat, 2006). Perceived privacy risk also has negative impacts on trust in e-transactions (Dinev and Hart, 2006). Therefore, this study puts forward the hypothesis:

H5: *Perceived risks of information participation have a significant negative effect on trust in AI-based medical consultation.*

2.2.2 Consequence of Trust

Information participation behavior in this research context refers to the extent to which users interact with platforms on relevant health information in the process of AI-based medical consultation, including providing, posting and giving responses. Trust is the most critical factor in promoting positive attitudes toward AVs (Zhang et al., 2019) and predicting users' acceptance behavior of various information systems, including e-commerce (Gefen et al., 2003), educational software (Ejdys, 2018), e-government (Shareef et al., 2011), and health information systems (Andrews et al., 2014). Furthermore, it has been mentioned as an important antecedent that influences consumer acceptance of AI-supported services (Ostrom et al., 2019). It indicates that potential consumers must engender trust to overcome risk and uncertainty perceptions and subsequently use these AI-supported services (Zhang et al., 2019). However, the role of trust in AI-based medical consultation has yet been determined. Therefore, we propose the following:

H6: *Trust has a significant positive effect on information participation behavior in AI-based medical consultation.*

2.3 The Moderating Role of Gender

Previous studies have found that gender, one of the most basic individual characteristics, significantly affects different decision-making processes of males and females (Zhou et al., 2014). From the social role theory, males and females play different social roles due to different social and cultural expectations, which affect their social behavior (Archer, 1996). Many research results in different backgrounds have shown the impact of gender differences on user behavior, such as information disclosure behavior in LBS behavior (Y. Li et al., 2021), continuous use behavior of Facebook (Lin and Wang, 2020), online purchase behavior (Wang and Chou, 2014; Zhang et al., 2021), mobile payment (Wang et al., 2022), and computer security behavior (Verkijika, 2019).

The issue of gender differences has attracted widespread attention in research on the cognition, acceptance, and adoption of AI-based products. However, the results of the different studies are completely inconsistent (Cirillo et al., 2020; Kassens-Noor et al., 2021). For example, Xiang et al. (2020) found that males and females had different acceptances of medical AI, and female participants had significantly lower knowledge of AI than male participants (Diaz et al., 2021). The same conclusion is found in studies on automatic driving, which claim that men are more likely to accept automatic driving technology than females and are less concerned about the negative effects associated with autonomous driving (Cunningham et al., 2019). Gallimore et al. (2019) studied gender differences in the use of automated robots and found that compared with males, females had higher trust in robots. The same conclusion is found in discussing AI in the development of smart cities; the impact of AI on the development of smart cities is more important to females. Furthermore, studies have found gender differences in adopting medical technology, with widely differing conclusions. For example, Balapour et al. (2019) found that gender had no significant effect on the willingness to adopt mobile medical apps. However, Zhang et al. (2014) found that gender adjusted the impact of various factors in threat and response assessment on attitudes toward using m-health to varying degrees. Females perceived susceptibility and severity have a more positive impact on attitudes than males, so they are more likely to use m-health to ensure their health. However, Alam et al. (2020) found that compared with women, men showed a stronger willingness to adopt mobile devices. Based on the above analysis, we have reason to believe that gender differences also exist in AI-based medical consultation.

Therefore, we propose as follows:

H7: *Gender moderates the relationship between perceived information control and benefits of information participation.*

H8: *Gender moderates the relationship between perceived information control and risks of information participation.*

H9: *Gender moderates the relationship between perceived benefits and risks of information participation.*

H10: *Gender moderates the relationship between perceived benefits of information participation and trust in AI-based medical consultation.*

H11: *Gender moderates the relationship between perceived risks of information participation and trust in AI-based medical consultation.*

H12: *Gender moderates the relationship between trust in AI-based medical consultation and information participation*.

Figure 1 shows the research model of this study. Age, income, education, and experience are control variables in the model.

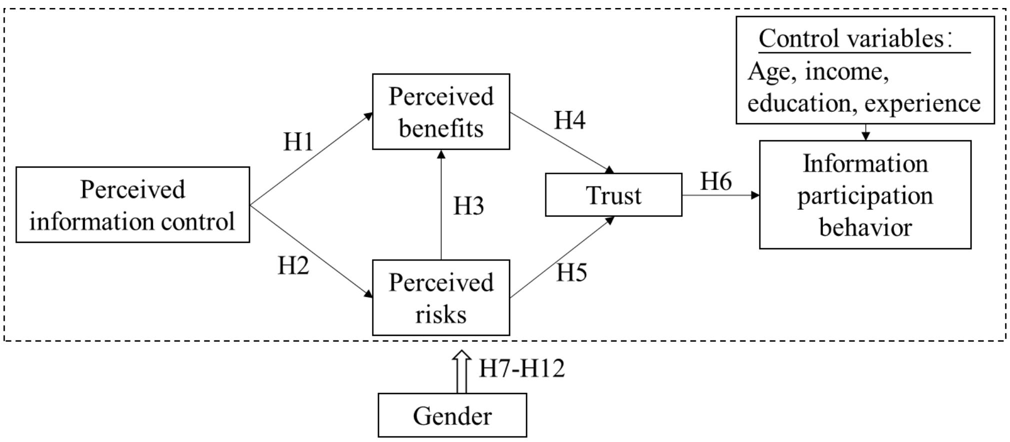


Figure 1: Research Model

3. Research Methodology

3.1 Measurements

The measurement items were derived from previous studies and adjusted appropriately for the context of this study. These items were measured using 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The measures for dependent variable information participation intention were adapted from Kamboj and Rahman (2017); the measures for perceptual information control were adapted from Alge et al. (2006); the measures for perceived benefit were adapted from Davis (1989); the measures for perceived risks were adapted from Cheng et al. (2021); while the measures for trust were adapted from Kankanhalli et al. (2005). Then the measurements were translated, in parallel, into Chinese by two groups of Ph.D students majoring in IS. Subsequently, they were asked to discuss their translations simultaneously, item by item, to ensure the quality of the Chinese questionnaire. Based on their feedback, we adjusted the questionnaire. The operationalization and sources of the scale items are shown in Table 1.

The research questionnaire was divided into three parts: the first part showed the identity information of the investigator, the definition of the survey subject, and the survey purpose; the second part measured participant's demographic information, including gender, age, education level, occupation, monthly income, and experience in AI-assisted medical consultation; the third part included items measuring constructs in the proposed research model, including perceived control, perceived benefits, perceived risks, trust, and information participation.

Table 1: Measurement of Constructs

Constructs		Items	Source
Perceptual information control (PIC)	PIC1	On an intelligent consultation platform, I can control who reads my personal information	Alge et al. (2006)
	PIC2	The intelligent consultation platform allows me to decide how to release my personal information to others	
	PIC3	On an intelligent consultation platform, I determine how the platform uses my personal information	
Perceived benefits (PB)	PB1	Using AI technology to collect information can improve the quality of intelligent consultation services	Davis (1989)
	PB2	Using AI technology to collect information can improve the efficiency of intelligent consultation services	
	PB3	I think information gathering based on AI technology is useful	
Perceived risk (PR)	PR1	Providing identification information based on AI technology would make my identification information to be used illegally	Cheng et al. (2021)
	PR2	Someone would use my identity for illegal purposes if I provide my identification information based on AI technology	
	PR3	The identity information I provide based on AI technology could lead to unauthorized access to my bank or credit card account	
Trust (TRU)	TRU1	I think the intelligent consultation platform can fulfill its promise, abide by the privacy protection policy, and keep my health information confidential	Kankanhalli et al. (2005)
	TRU2	I think the intelligent consultation platform can make reasonable and appropriate use of my personal information	
	TRU3	I think the intelligent consultation platform is trustworthy	
Information participation behavior (IPB)	IPB1	I frequently provide my personal health information to the intelligent consultation platform	Kamboj and Rahman (2017)
	IPB2	I often provide useful health information to other users on the intelligent consultation platform	
	IPB3	I often post and provide responses on the intelligent consultation platform	

3.2 Data Collection

We used Sojump (http://www.sojump.com), an established Chinese website providing online survey services (Y. Li et al., 2021; Zhang et al., 2017), to collect data. The questionnaire was sent to users of AI-based medical consultation platforms, such as “Ali health,” “Ping An Health,” “Xuexi Qiangguo,” and “Chunyu Doctor”. AI-based medical consultation takes the medical knowledge map as its core and simulates the real doctor-patient interaction process. Patients complete the consultation through human-computer interaction on the mobile phone or PC. Through intelligent interactive consultation, the AI-based consultation platform will automatically collect and comprehensively analyze patients' symptoms, signs, medical history and other information, and finally generate a diagnosis report, such as predicting disease for self-consultation or recommending doctors for consultation, for the patient's reference. Figure 2 shows an example of a user consulting Ali health’s Quark AI for a headache.

Figure 2: An Example of Consultation between the User and Quark AI

The data collection process took place in October 2021. Before filling out the questionnaires, subjects were introduced to AI-based medical consultation (i.e., the definition of AI-based medical consultation and its functions), and some AI-based medical consultation pictures were shown to ensure that respondents had some understanding of the AI-based medical consultation. To ensure that only respondents who had used AI-based medical consultation were included, we put a pre-screening question to ask them if they had used AI-based medical consultation. Only those who answered "yes" were asked to continue with the questionnaire. In total, 494 responses were received, all of which had unique IP addresses and information about submission time. Invalid questionnaires were removed using the following criteria: (1) The respondents gave the same answers to all questions (e.g., all 1 or all 5); and (2) The respondents completed the questionnaire in less than 100 s or more than 60 min, as suggested in the previous research (Chen and Zahedi, 2016). The final survey sample consisted of 470 responses. The subjects' demographic characteristics are shown in Table 2.

Table 2: Sample Descriptive Statistics

Characteristic		Frequency	Percentage (%)
Gender	Male	194	41.28
	Female	276	58.72
Age	Less than 18	19	4.04
	18–30 yr old	289	61.49
	31–40 yr old	133	18.3
	41–50 yr old	22	4.86
	More than 51 yr old	7	1.49
Education level	High school or less	31	6.6
	College	43	9.15

	Bachelor's degree	341	72.55
	Master's and PhD	55	11.70
Monthly income (RMB)	2000 and below	89	18.94
	2001–4000	92	19.57
	4001–6000	189	40.21
	6001 and above	100	21.28

4. Analysis and Results

A two-step process was used to analyze the collected data. First, we evaluated the measurement model by verifying its reliability, convergent, and discriminant validities. Second, we used SmartPLS 3.0 to examine the strength and direction of the relationships between constructs. SmartPLS 3.0 was used to analyze the data for the following reasons: first, PLS-SEM is a second-generation technique that can model relationships among multiple predictors and dependent variables (Chin, 1998). Particularly, it can simultaneously measure the reliability and validity of the constructs (by estimating loadings) and the causal relationships among constructs (Fornell and Bookstein, 1982). Additionally, PLS-SEM does not impose strict requirements of multigroup normality and asymptotic assumption in relative to the conventional CB-SEM (Hair et al., 2017), as is the case in this study. Here, a comparison needs to be conducted between the male and female groups.

4.1 Common Method Deviation Test

Harman's (1976) single-factor test method was adopted to test the common method variance (CMV). This test involves an exploratory factor analysis of all items to determine whether most of the variance can be explained by a general factor (Podsakoff and Organ, 1986). The factor analysis results showed that five factors with eigenvalues greater than 1 were precipitated when there was no rotation, and the first factor had a variance explanation rate of 30.61%. A judgment criterion of less than 40% indicates that no serious common method bias in the data was recorded (Podsakoff and Organ, 1986).

4.2 Measurement Model Analysis

We used several criteria (such as reliability, convergent validity, and discriminant validity) to evaluate the measurement model. Reliability can be observed through Cronbach's alpha and composite reliability (CR). Table 3 shows that Cronbach's α coefficients of most constructs are greater than 0.7, except for perceived benefits of 0.602, which remains within the acceptable range. CR value obtained was greater than 0.789. This implies that the measurement model is adequately reliable (Fornell and Larcker, 1981). Table 3 shows that all item loadings were greater than 0.70, and average variance extracted (AVE) was greater than 0.555, indicating that the measurement model has good convergence validity. Furthermore, we also compared the square of AVE with the correlations among latent variables (as reported in Table 3). The square values of AVE were greater than the pairwise correlations, indicating that the measurement model has sufficient discriminant validity (Gefen and Straub, 2005). Also, discriminant validity is established since the heterotrait-monotrait ratio (HTMT) pairs of latent variables are all below the threshold of 0.85 (Henseler et al., 2015) (see Table 4).

Table 3: Construct Reliability and Validity for the Full Sample (N = 470)

	Cronbach' alpha	CR	AVE	PIC	PB	PR	Trust	IP
Perceived information control (PIC)	0.803	0.878	0.707	**0.841**				
Perceived benefits (PB)	0.602	0.789	0.555	0.153	**0.745**			
Perceived risk (PR)	0.854	0.911	0.773	−0.129	−0.276	**0.879**		
Trust	0.741	0.853	0.659	0.392	0.487	−0.437	**0.812**	
Information participation behavior (IPB)	0.706	0.834	0.627	0.332	0.295	−0.215	0.491	**0.792**
Factor loading range				0.781–0.850	0.712–0.772	0.857–0.889	0.768–0.853	0.760–0.837

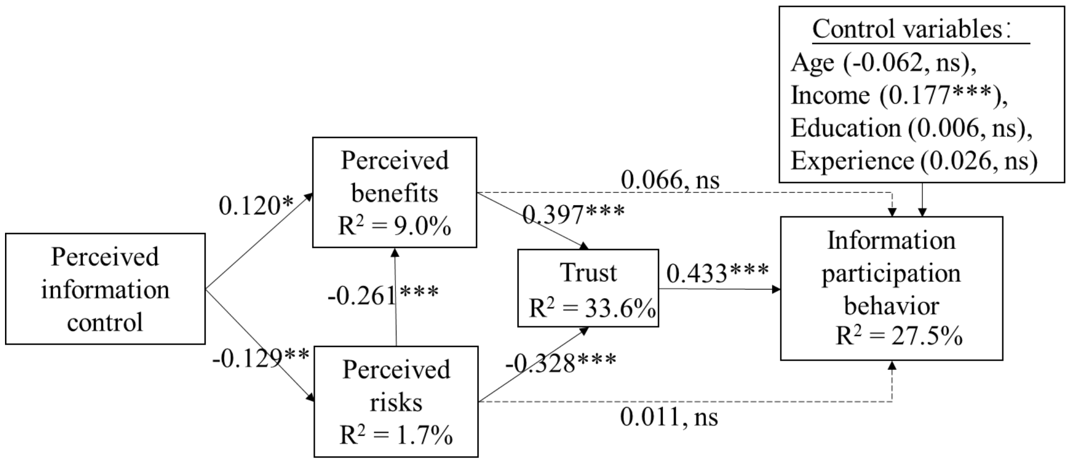
Note: Bold diagonal numbers are the square roots of AVE, and the non-diagonal numbers are the correlation coefficients between the dimensions.

Table 4: HTMT Ratio of Correlations

Constructs	PIC	PB	PR	Trust
Perceived information control (PIC)				
Perceived benefits (PB)	0.208			
Perceived risk (PR)	0.142	0.373		
Trust	0.507	0.724	0.539	
Information participation behavior (IPB)	0.459	0.447	0.258	0.659

4.3 Structural Model Analysis for the Full Sample

A bootstrap algorithm was used to test the significance of the path coefficient of the structural equation and explanatory power (Sia et al., 2009). The test results, as shown in Figure 3, indicate that perceived information control has a significantly positive effect on perceived income (β = 0.120, p = 0.016), supporting H1. Furthermore, it has a significantly negative effect on perceived risk (β = −0.129, p = 0.007), supporting H2. Perceived risk has a significant negative effect on perceived benefits and trust (β = −0.261, p = 0.000; β = −0.328, p = 0.000), supporting H3 and H5, respectively. Additionally, perceived benefits have a significant positive effect on trust (β = 0.397, p = 0.000), supporting H4. Also, trust has a significant positive effect on information participation behavior (β = 0.433, p = 0.000), supporting H6.



Notes: ***p < 0.001; **p < 0.01; *p < 0.05 (two-tailed); ns (nonsignificant)

Figure 3: Results of Structural Model Analysis for the Full Sample

Concerning the explanatory power of the research model, we explained 33.6% and 27.5% of the variation in trust and IP, respectively. Additionally, Table 5 includes the overall fit evaluation of the estimated models. All values of discrepancy measures were below the 95% quantile of their corresponding reference distribution (HI_{95}), indicating that the estimated model was not rejected at a 5% significance level. Moreover, the computed SRMR of 0.045 is less than the cut-off value of 0.080, indicating an acceptable model fit (Hair et al., 2018).The evaluation of the estimated model's overall fit indicates that the proposed research model is true and is a research model that allows us to explain theoretically how and why users participate in and use AI-assisted medical consultation (Benitez et al., 2020).

Table 5: Overall Model Fit Evaluation of the Estimated Models.

Discrepancy	Value for the estimated model	HI_{95} for the estimated model	Conclusion
SRMR	0.045	0.050	Supported
d_{ULS}	0.393	0.478	Supported
d_G	0.210	0.228	Supported

The mediating role of trust was determined based on a decision tree documented in Nitzl et al. (2016). As shown in Table 6, trust fully mediated the effects of perceived benefits and perceived risks on information participation behavior.

Table 6: Results of Mediating Effect Tests of Trust

Direct effect		Mediating effect		Mediating role of trust
PB→IPB	0.066	PB→Trust→IPB	0.172***	Full mediation
PR→IPB	0.011	PR→Trust→IPB	-0.142***	Full mediation

Note: PB, Perceived benefits; PR, Perceived risks; IPB, Information participation behavior.
***p < 0.001; **p < 0.01

4.4 Multi-Group Measurement Invariance Test

To subsequently compare groups, we tested the measurement invariants of each latent variable among male and female groups with SmarPLS3.0, using the method for measuring the invariance of composite models proposed by Hair et al. (2014). The measurement invariance test includes configural and compositional invariances. First, since we used the same measurement scale used in data collection, the measurement of male and female meets the requirement of configural invariance. Second, using the Permutation algorithm, the correlation coefficients of inter-group scores of all potential variables were within 95% confidence interval (perceived information control: r = 0.996, 95% CI = [0.945, 1]; perceived benefits: r = 0.996, 95% CI = [0.982, 1]; perceived risks: r = 0.999, 95% CI = [0.997, 1]; Trust: r = 0.999, 95% CI = [0.997, 1]; IP: r = 0.994, 95% CI = [0.993, 1]), indicating that the measurement invariance between male and female groups meets the requirement of compositional invariance.

4.5 Multiple Group Analysis

The path coefficients for the female and male groups are shown in Figure 4. The results show that the path coefficients are different among different groups. To further determine whether these differences are significant, $t_{spooled}$ statistics and corresponding p-values of the path coefficient of male and female groups were calculated (Ahuja and Thatcher, 2005; Keil, Wei, et al., 2000), and reported in Table 7. These results showed that the influence of perceived information control on perceived benefits was significantly greater for the male group than for the female group （$\beta_{female} = 0.069$, p = 0.254; $\beta_{male} = 0.186$, p = 0.027; $t_{spooled} = 17.738$, p = 0.000）, supporting H7; The effect of perceived benefits on trust was also significantly greater for the male group than for the female group （$\beta_{female} = 0.367$，p = 0.000; $\beta_{male} = 0.433$, p = 0.000; $t_{spooled} = 9.587$, p = 0.000）, supporting H10. However, the relationships between perceived information control and perceived risk（$\beta_{female} = -0.157$, p = 0.017; $\beta_{male} = -0.104$, p = 0.273; $t_{spooled} = 7.181$, p = 0.000）, perceived risks and perceived benefits （$\beta_{female} = -0.332$, p = 0.000; $\beta_{male} = -0.190$, p = 0.024; $t_{spooled} = 22.290$, p = 0.000）, and perceived risks and trust（$\beta_{female} = -0.342$ p = 0.000; $\beta_{male} = -0.313$, p = 0.000; $t_{spooled} = 4.718$, p = 0.000） showed stronger negative effects for females than for males, thus supporting H8, H9, and H11. However, the relationship between trust and information participation behavior has no significant difference between male and female （$\beta_{female} = 0.443$ p = 0.000; $\beta_{male} = 0.432$, p = 0.000; $t_{spooled} = 1.312$, p = 0.190）, thereby not supporting H12.

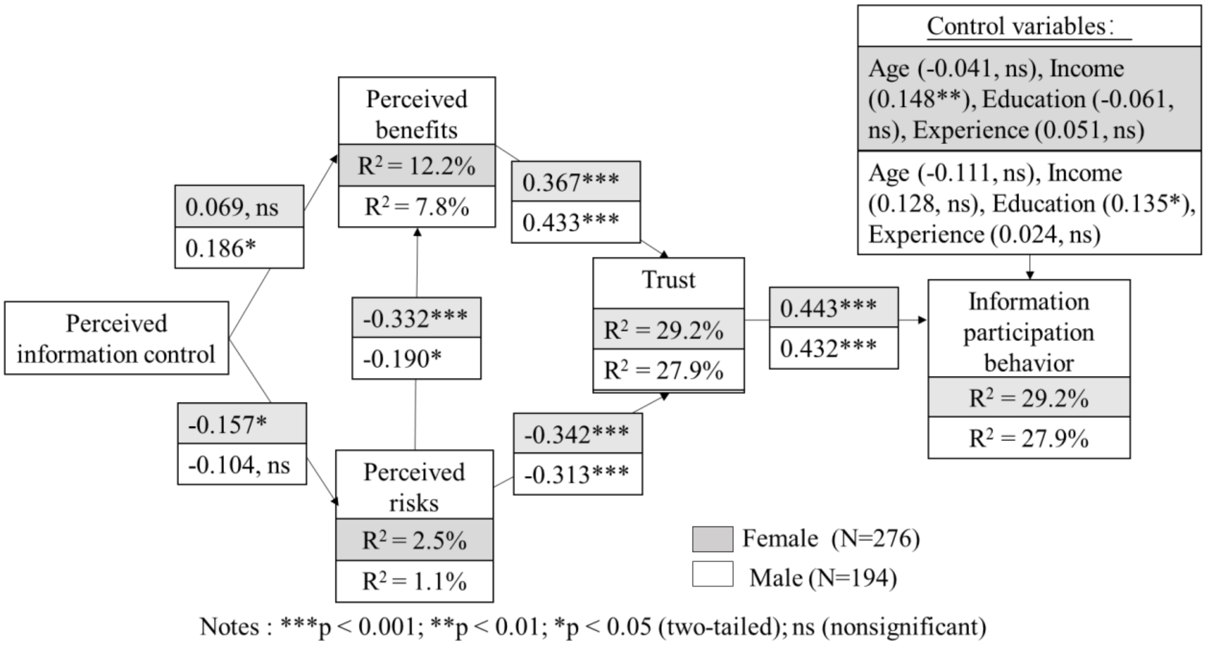


Figure 4: Results of Structural Model Analysis for Female and Male Group Samples

Table 7: Path Coefficient Comparison Statistics between Females (N = 276) and Males (N=194)

Path	Path coefficients		$t_{spooled}$	Hypothesis support
	Female	Male		
H7: Perceived information control →Perceived benefits	0.069	0.186*	17.738***	Supported
H8: Perceived information control →Perceived risk	−0.157*	−0.104	7.181***	Supported
H9: Perceived risk →Perceived benefits	−0.332***	−0.190*	22.290***	Supported
H10: Perceived benefits →Trust	0.367***	0.433***	9.587***	Supported
H11: Perceived risks →Trust	−0.342***	−0.313***	4.718***	Supported
H12: Trust →information participation behavior	0.443***	0.432***	1.312	Not supported

Notes: ***p < 0.001, **p < 0.01, *p < 0.05. The formula for computing the $t_{spooled}$ significance of the differences in the path coefficients for the various subgroup samples is derived from Keil, Tan, et al. (2000) (see Appendix A for details)

5. Discussion and Implications

This study proposes a theoretical research model to examine the roles of privacy calculus theory, trust, and gender in information participation of AI-based medical consultation platforms. We investigate how perceived information control relates to perceived benefits and risks; how perceived benefits and risks relate to trust in AI-based medical consultation platform; how trust relates to information participation; and how the gender of users can moderate the results.

First, the study examines the applicability of the privacy calculus theory in AI-based medical consultation. Specifically, our results indicate that perceived information control directly increases perceived benefits and reduces perceived risks. In addition, control indirectly increases perceived benefits through reducing perceived risks. In the healthcare context, Princi and Krämer (2020) postulated that control created a sense of security, which led to a higher perception of benefits and a lower assessment of privacy risks. These results indicate that when an AI-based medical consultation platform allows more control of private data, it is likely that users will ignore risks and underestimate potential privacy risks. At the same time, Hajli and Lin (2016) assumed that when users were less concerned about their data collection, they had more perceived benefits and a more positive attitude towards the information participation.

Second, our results show that trust is a significant determinant in influencing behavioral intention to participate in information disclosure in AI-based medical consultation. This result agrees with the evidence reported in other research, such as AVs and e-commerce services (Kamal et al., 2019; Kim and Peterson, 2017) and smart healthcare services (Liu and Tao, 2022). Note that trust completely mediates the relationships between perceived benefits and information participation, and between perceived risks and information participation, indicating the critical role of trust in determining an acceptable behavior of AI-based healthcare services.

Third and more significantly, our findings indicate the gender variances in terms of impacts of strengths of privacy calculus on trust in platforms. Specifically, the relationships between perceived information control and benefits and perceived benefits and trust are stronger for males than for females. However, the relationships between perceived information control and risks and perceived risks and trust are stronger for females than for males. These results indicate that males are more task-oriented and easily affected by utility and performance, whereas females are more sensitive to risks and easily affected by perceived risks. This is congruent with previous studies which argue that female are more likely to show risk-averse behavior by taking active behaviors to avoid risks and ensure their own safety (Powell and Ansic, 1997). At the same time, males are more likely to show a preference for task-oriented results (Venkatesh et al., 2012). This study also further confirms that the negative impact of perceived risks on perceived benefits is stronger for females than for males.

Finally, the moderating effect of gender in trust on users' information participation is insignificant, which is in line with the findings of Heidarian (2019) and contradicts others' findings (Abubakar et al., 2017). Abubakar et al. (2017) found that when females trusted a destination, they tended to have higher intention to revisit than males, which also conforms to the idea of females being more risk-averse. The reason for this inconsistency may be that the information users disclose on the platform during the intelligent consultation is largely related to personal health privacy. Once leaked or illegally used, it causes serious property loss or even threatens personal dignity, for which reason, males also have a strong awareness of risk-averse. Second, in the medical consultation context, the main objective of users on the platform is to get accurate diagnoses of their illness, timely alleviate it, and perform/schedule the next treatment. If the medical treatment results are inaccurate or wrong, the illness will either remain mild, or progressed to a severe case that eventually endangers their lives. As a result, users care more about trust in the platform than they do about service satisfaction. Both male and female users who pay more attention to perceived benefits and perceived risks, respectively, will choose intelligent consultation platforms that provide more real information and hold more reliable activities for medical treatment.

5.1 Theoretical Implications

First, this study extends the privacy calculus theory to AI medical technology context. Some of the previous studies on privacy and information participation are conducted in different context, such as utilitarian technology context (e.g., Xu et al., 2009) and hedonic technology context (e.g., Sun et al., 2015). In this study, in view of the contextual differences, we consider information control when users cogitate the tradeoff between perceived benefits and risks. The findings suggest future researchers pay attention to the contextual differences and develop context-specific models based on these differences.

Second, our findings contribute to the existing literature by exploring how perceived benefits and risks are associated with trust, and how trust is related to information participation in AI-based medical consultation. Previous studies on information disclosure have mainly investigated the impact of perceived benefits and risks on intention or behavior, ignoring the role of trust (Cheng et al., 2021; Sun et al., 2021; Sun et al., 2015; Xu et al., 2009). Although previous studies on privacy issues related to AI technology have begun to show concern about trust (Bawack et al., 2021; Wu et al., 2012), this study further demonstrates that trust plays an important role in determining information participation behavior in AI-based medical consultation. It balances the perceived benefits and risks, and bridges the relationship between perceived benefits and risks and information participation behavior.

Third, this study extends this line of research by proposing that the effects of these privacy calculus and trust on information participation are contingent on users' gender. The gender differences in the information participation behavior have been rarely investigated (Sun et al., 2015). Even though some studies have explored the moderating role of gender in understanding the impacts of perceived benefits on intention (Sun et al., 2015; Venkatesh et al., 2012), their conclusions differ. For example, Sun et al. (2015) found that the impacts of benefits on intention were stronger for females than for males, while Venkatesh et al. (2012) stated that the relationship between benefits and intention was stronger for males than for females. To solve the inconsistency, we consider two stages by stating that males and females may think differently at the privacy-trust stage and the trust-behavior stage. Our results show that females place more stress on perceived risks while males stress perceived benefits more at the privacy-trust stage. At the trust-behavior stage, there are no considerable differences between males and females. Thus, a better understanding on the impacts of privacy calculus on behavior requires a distinction between the privacy-trust stage and the trust-behavior stage.

5.2 Practical Implications

First, perceived information control is a driving force for user information participation behavior. The process of AI-based medical consultation should follow a special privacy management module, and pay more attention to the design of information management, permission statement management and interaction management. On the one hand, the smart medical consultation platform should adopt fair and transparent information processing methods, formulate sound privacy protection policies, clarify the purpose and use of health information collection, and provide users with clear privacy disclosure options, such as allowing them to choose the types of information to be disclosed and the objects to be shared, so as to show respect for and importance of user privacy, thus eliminating users' privacy concerns. On the other hand, the smart medical consultation platform should formulate license statement terms that are easy for users to understand, and have friendly default Settings, provide users with privacy setting functions, promote users' independent management of personal information, give full play to the positive effect of license statement management, and facilitate users to update and control information. These measures will allow users to perceive that their private information is still under control and that there is no risk of privacy loss.

Second, this study verifies that user behavior is affected by gender and explains the reasons for the differences in users’ information participation behavior under the same situation, which is of reference significance for men and women to receive more equal data security protection in the era of big data in the future. In some cases, perceived benefits have less effect on user information engagement behavior than perceived risks, and in others the opposite is true. As the theory of Communication Privacy Management (CPM) suggests: males and females define their privacy boundaries differently and develop a unique set of privacy management strategies. The platform needs to learn to accurately grasp and take advantage of this difference, and carry out different inquiry processes for different users. That is, the privacy policy of the inquiry interface for female users should be more detailed and prominent, and ensure that they can use more privacy Settings to manage their privacy, such as setting sensitive personal data to only private visibility, and clearing the record after the inquiry. For the males, the interface should be more concise, convenient, and easy to operate, to meet the purpose of consultation while involving less privacy control.

Finally, similar to intelligent consultation in the medical field, intelligent services in the field of e-commerce, intelligent classroom in the field of education, and intelligent security in the field of urban construction are all based on AI. The paradoxical role of emerging technologies causes users anxiety and hesitation when using intelligent services. Based on the findings of this study, platform operators must be clear that users' trust in the platform is the premise of their information participation, so the platform should try to overcome the dilemma of low level of trust in the platform. Both perceived benefits and perceived risks significantly affect users' trust in the platform and information participation behavior. Platform managers should cultivate and consolidate users’ trust, for example, by improving service quality and complaint channels. At the same time, service providers can improve the application of AI technology to make intelligent services more professional, more personalized and interactive, which can directly enhance users' trust in the platform.

5.3 Limitations and Suggestions for Future Research

Inevitably, our study includes some limitations. First, this paper discusses the influence of gender on users’ information participation behavior. There are many boundary conditions in this process, and there are many levels of user characteristics. In addition to gender, relevant factors such as age, personality, and cultural background should be considered. For example, users with higher education levels may consider more risks when using the consultation platform, making it more difficult to share their health privacy information. Further investigations should go deeper into this concern and consider other personal characteristics, such as age, health condition and experience, etc. Second, our survey only targeted users from mainly AI-based medical consultation platforms. This includes a feasible selection bias. To generalize the findings of this study, future research should collect data across various countries. Finally, this survey adopted a questionnaire that asked people to rate their feelings when using the intelligent consultation service platform, which was highly subjective and did not set up real scenes to truly induce users’ emotions. In the future, real scenarios can be set to arouse people’ real emotions to remedy this defect.

6. Conclusions

The advent of AI techniques enables the increasing application in various industries and scenarios. However, the success of their implementation highly depends on users’ trust and information participation, especially in smart healthcare services. The present study highlights the role of trust in mediating the relationship between privacy-related antecedent and information participation behavior, privacy calculus in influencing the information participation behavior. The research model is empirically tested, showing that trust is the key path in shaping user information participation, which fully mediates the effects of privacy-related antecedent on user information participation. In addition, this study demonstrates that users' gender is an important moderator of the relationships at the privacy-trust stage, but not at the trust-behavior stage. The findings indicate that users' gender should be considered at different stages when developing smart healthcare services for specific populations. The study offers important theoretical and practical implications for better design, development, and implementation of smart-related services.

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REFERENCES

Abubakar, A. M., Ilkan, M., Meshall Al-Tal, R., & Eluwole, K. K. (2017). EWOM, revisit intention, destination trust and gender. *Journal of Hospitality and Tourism Management*, *31*, 220-227. https://doi.org/https://doi.org/10.1016/j.jhtm.2016.12.005

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427-445. https://doi.org/10.1007/s12525-020-00414-7

Ahuja, M. K., & Thatcher, J. B. (2005). Moving beyond intentions and toward the theory of trying: Effects of work environment and gender on post-adoption information technology use. *MIS Quarterly*, *29*(3), 427-459.

Akter, S., D'Ambra, J., & Ray, P. (2011). Trustworthiness in mHealth information services: An assessment of a hierarchical model with mediating and moderating effects using partial least squares (PLS). *Journal of the American Society for Information Science and Technology*, *62*(1), 100-116.

Alam, M. Z., Hoque, M. R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. *International Journal of Information Management*, *50*, 128-143.

Alge, B. J., Ballinger, G. A., Tangirala, S., & Oakley, J. L. (2006). Information privacy in organizations: Empowering creative and extrarole performance. *Journal of Applied Psychology,*, *91*(1), 221-232. https://doi.org/10.1037/0021-9010.91.1.221

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, *114*, 106548. https://doi.org/https://doi.org/10.1016/j.chb.2020.106548

Ameen, N., Tarhini, A., Shah, M. H., & Madichie, N. O. (2019). Employees' behavioural intention to smartphone security: A gender-based, cross-national study. *Computers in Human Behavior*, *104*, 106184.

Andrews, L., Gajanayake, R., & Sahama, T. (2014). The Australian general public's perceptions of having a personally controlled electronic health record (PCEHR). *International Journal of Medical Informatics*, *83*(12), 889–900.

Antheunis, M. L., Valkenburg, P. M., & Peter, J. (2010). Getting acquainted through social network sites: Testing a model of online uncertainty reduction and social attraction. *Computers in Human Behavior*, *26*(1), 100-109.

Archer, J. (1996). Sex differences in social behavior. Are the social role and evolutionary explanations compatible? *American Psychologist*, *51*(9), 909-917.

Balapour, A., Reychav, I., Sabherwal, R., & Azuri, J. (2019). Mobile technology identity and self-efficacy: Implications for the adoption of clinically supported mobile health apps. *International Journal of Information Management*, *49*, 58-68.

Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2021). Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis. *International Journal of Information Management*, *58*, 102309.

Belli, L., Schwartz, M., & Louzada, L. (2017). Selling your soul while negotiating the conditions: From notice and consent to data control by design. *Health and Technology*, *7*(4), 453-467. https://doi.org/10.1007/s12553-017-0185-3

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, *57*(2), 103168.

Bostrom, R. P., Olfman, L., & Sein, M. K. (1990). The importance of learning style in end-user training. *MIS Quarterly*, *14*(1), 101-119.

Chen, T., Guo, W., Gao, X., & Liang, Z. (2021). AI-based self-service technology in public service delivery: User experience and influencing factors. *Government Information Quarterly*, *38*(4), 101520. https://doi.org/https://doi.org/10.1016/j.giq.2020.101520

Cheng, X., Su, L., Luo, X. R., Benitez, J., & Cai, S. (2021). The good, the bad, and the ugly: Impact of analytics and artificial intelligence-enabled personal information collection on privacy and participation in ridesharing. *European Journal of Information Systems*, *31*(3), 339-363.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, *22*(1), vii-xvi.

Chiu, C. M., Wang, E. T. G., Fang, Y. H., & Huang, H. Y. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: The roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal*, *24*(1), 85–114.

Cirillo, D., Catuara-Solarz, S., Morey, C., Guney, E., Subirats, L., Mellino, S., Gigante, A., Valencia, A., Rementeria, M. J., Chadha, A. S., & Mavridis, N. (2020). Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare. *NPJ Digit Medicine*, *3*, 81. https://doi.org/10.1038/s41746-020-0288-5

Ćirković, A. (2020). Evaluation of four artificial intelligence–assisted self-diagnosis apps on three diagnoses: Two-year follow-up study. *Journal of Medical Internet Research*, *22*(12), e18097.

Culnan, M. J., & Armstrong, P. K. (1999). Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organization Science*, *10*(1), 104-115.

Cunningham, M. L., Regan, M. A., Horberry, T., Weeratunga, K., & Dixit, V. (2019). Public opinion about automated vehicles in Australia: Results from a large-scale national survey. *Transportation Research Part A: Policy and Practice*, *129*, 1-18. https://doi.org/10.1016/j.tra.2019.08.002

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

DeSouza, M. L. M., Lopes, G. A., Branco, A. C., Fairley, J. K., & Fraga, L. A. D. O. (2021). Leprosy screening based on artificial intelligence: Development of a cross-platform app. *JMIR mHealth and uHealth*, *9*(4), e23718.

Dhir, A., Pallesen, S., Torsheim, T., & Andreassen, C. S. (2016). Do age and gender differences exist in selfie-related behaviours? *Computers in Human Behavior*, *63*, 549-555. https://doi.org/https://doi.org/10.1016/j.chb.2016.05.053

Diaz, O., Guidi, G., Ivashchenko, O., Colgan, N., & Zanca, F. (2021). Artificial intelligence in the medical physics community: An international survey. *Physica Medica*, *81*, 141-146. https://doi.org/10.1016/j.ejmp.2020.11.037

Dienlin, T., & Metzger, M. J. (2016). An extended privacy calculus model for SNSs: Analyzing self-disclosure and self-withdrawal in a representative US sample. *Journal of Computer-Mediated Communication*, *21*(5), 368-383.

Dienlin, T., & Trepte, S. (2015). Is the privacy paradox a relic of the past? An in-depth analysis of privacy attitudes and privacy behaviors. *European Journal of Social Psychology*, *45*(3), 285-297.

Dinev, T., & Hart, P. (2005). Internet privacy concerns and social awareness as determinants of intention to transact. *International Journal of Electronic Commerce*, *10*(2), 7-29.

Dinev, T., & Hart, P. J. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research*, *17*(1), 61-80.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63-71.

Ejdys, J. (2018). Building technology trust in ICT application at a university. *International Journal of Emerging Markets*, *13*(5), 980-997.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies*, *59*(4), 451-474.

Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, *19*(4), 440-452.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.

Fox, G., & Connolly, R. (2018). Mobile health technology adoption across generations: Narrowing the digital divide. *Information Systems Journal*, *28*(6), 995-1019.

Furlong, A. (1998). Should we or shouldn't we? Some aspects of the confidentiality of clinical reporting and dossier access. *International Journal of Psycho-Analysis*, *79*, 727-739.

Gallimore, D., Lyons, J. B., Vo, T., Mahoney, S., & Wynne, K. T. (2019). Trusting robocop: Gender-based effects on trust of an autonomous robot. *Frontier in Psychology*, *10*, 482. https://doi.org/10.3389/fpsyg.2019.00482

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51-90.

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.

Guo, X., Zhang, X., & Sun, Y. (2016). The privacy–personalization paradox in mHealth services acceptance of different age groups. *Electronic Commerce Research and Applications*, *16*, 55-65.

https://doi.org/https://doi.org/10.1016/j.elerap.2015.11.001

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent device use in service delivery. *International Journal of Information Management*, *49*, 157-169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Hair, J. F., Hult, G. T. M., & Ringle, C. M. (2014). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage.

Hair, J. F., Marko, S., Ringle, C. M., & Gudergan, S. P. (2018). *Advanced issues in partial least squares structural equation modeling(PLS-SEM)*. Sage.

Hair, J. F., Matthews, L. M., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123.

Hajli, N., & Lin, X. (2016). Exploring the security of information sharing on social networking sites: The role of perceived control of information. *Journal of Business Ethics*, *133*(1), 111-123. https://doi.org/10.1007/s10551-014-2346-x

Heidarian, E. (2019). The impact of trust propensity on consumers' cause-related marketing purchase intentions and the moderating role of culture and gender. *Journal of International Consumer Marketing*, *31*(4), 345-362. https://doi.org/10.1080/08961530.2019.1575316

Henseler, J. R., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135.

Hew, J.-J., Lee, V.-H., Ooi, K.-B., & Lin, B. (2016). Mobile social commerce: The booster for brand loyalty? *Computers in Human Behavior*, *59*, 142-154.

Hong, & Ilyoo, B. (2015). Understanding the consumer's online merchant selection process: The roles of product involvement, perceived risk, and trust expectation. *International Journal of Information Management*, *35*(3), 322-336.

Hong, S., Kim, J., & Lee, H. (2008). Antecedents of use-continuance in information systems: Toward an inegrative view. *The Journal of Computer Information Systems*, *48*(3), 61-73.

Huang, J., Kumar, S., & Hu, C. (2018). Gender differences in motivations for identity reconstruction on social network sites. *International Journal of Human–Computer Interaction*, *34*(7), 591-602. https://doi.org/10.1080/10447318.2017.1383061

Hwang, Y. (2009). The impact of uncertainty avoidance, social norms and innovativeness on trust and ease of use in electronic customer relationship management. *Electronic Markets*, *19*(2-3), 89-98.

Jiang, J., Yang, M., Kiang, M., & Cameron, A. F. (2021). Exploring the freemium business model for online medical consultation services in China. *Information Processing & Management*, *58*(3), 102515.

Kamal, S. A., Shafiq, M., & Kakria, P. (2019). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society*, *60*, 101212.

Kamboj, S., & Rahman, Z. (2017). Measuring customer social participation in online travel communities: Scale development and validation. *Journal of Hospitality and Tourism Technology*, *8*(3), 432-464. https://doi.org/10.1108/JHTT-08-2016-0041

Kang, E. Y.-N., Chen, D.-R., & Chen, Y.-Y. (2023). Associations between literacy and attitudes toward artificial intelligence–assisted medical consultations: The mediating role of perceived distrust and efficiency of artificial intelligence. *Computers in Human Behavior*, *139*, 107529. https://doi.org/https://doi.org/10.1016/j.chb.2022.107529

Kankanhalli, A., Tan, B. C. Y., & Kwok-Kee, W. (2005). Contributing knowledge to electronic knowledge repositories: An empirical investigation. *MIS Quarterly*, *29*(1), 113-143.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15-25.

Kassens-Noor, E., Wilson, M., Kotval-Karamchandani, Z., Cai, M., & Decaminada, T. (2021). Living with autonomy: Public perceptions of an AI-mediated future. *Journal of Planning Education and Research*. https://doi.org/10.1177/0739456X20984529

Keil, M., Tan, B. C. Y., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly*, *24*(2), 299-325.

Keil, M., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly*, *24*(2), 299-325.

Kim, D., & Benbasat, I. (2006). The effects of trust-assuring arguments on consumer trust in Internet stores: Application of Toulmin's model of argumentation. *Information Systems Research*, *17*(3), 286.

Kim, Y., & Peterson, R., A. (2017). A meta-analysis of online trust relationships in e-commerce. *Journal of Interactive Marketing*, *38*, 44-54.

Kobsa, A. (2007). Privacy-enhanced personalization. *Communications of the ACM*, *50*(8), 24-33. https://doi.org/10.1145/1278201.1278202

Koirala, N. (2020). Trust and communication in a doctor patient relationship. *Birat Journal of Health Sciences*, *4*(3), 770.

Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. *Computers & Security*, *64*, 122-134.

Koohikamali, M., Gerhart, N., & Mousavizadeh, M. (2015). Location disclosure on LB-SNAs: The role of incentives on sharing behavior. *Decision Support Systems*, *71*, 78-87.

Lan, Y., & Yan, Y. (2017). The impact of trust, interaction, and empathy in doctor-patient relationship on patient satisfaction. *Journal of Nursing and Health Studies*, *2*(2), 1-7. https://doi.org/10.21767/2574-2825.100015

Laufer, R. S., & Wolfe, M. (1977). Privacy as a concept and a social issue: A multidimensional developmental theory. *Journal of Social Issues*, *33*(3), 22-42.

Lee, C.-H., Chen, C.-W., Chen, W.-K., & Lin, K.-H. (2021). Analyzing the effect of social support and customer engagement on stickiness and repurchase intention in social commerce: A trust transfer perspective. *Journal of Electronic Commerce Research*, *22*(4), 363-381.

Lee, C. S., Watson-Manheim, M. B., & Chudoba, K. M. (2014). Investigating the relationship between perceived risks in communication and ICT-enabled communicative behaviors. *Information & Management*, *51*(6), 688-699.

Lee, H., Park, H., & Kim, J. (2013). Why do people share their context information on Social Network Services? A qualitative study and an experimental study on users' behavior of balancing perceived benefit and risk. *International Journal of Human-Computer Studies*, *71*(9), 862-877. https://doi.org/https://doi.org/10.1016/j.ijhcs.2013.01.005

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, *46*(1), 50-80. https://doi.org/10.1518/hfes.46.1.50_30392

Lee, N., & Kwon, O. (2015). A privacy-aware feature selection method for solving the personalization–privacy paradox in mobile wellness healthcare services. *Expert Systems with Applications*, *42*(5), 2764-2771.

Li, M., Yin, D., Qiu, H., & Bai, B. (2021). A systematic review of AI technology-based service encounters: Implications for hospitality and tourism operations. *International Journal of Hospitality Management*, *95*, 102930. https://doi.org/https://doi.org/10.1016/j.ijhm.2021.102930

Li, Y., Mou, J., Ye, L., Long, J., & Huang, W. (2021). An empirical investigation of the utilitarian, social benefits in LBS information disclosure—the moderating effect of the gender based social role theory. *International Journal of Information Management*, *56*, 102243. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2020.102243

Lin, X., & Wang, X. (2020). Examining gender differences in people's information-sharing decisions on social networking sites. *International Journal of Information Management*, *50*, 45-56. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.05.004

Liu, J., Li, R., Li, L., Miao, S., & Du, W. (2020). *Chinese public's health awareness and behaviour during epidemic*. Retrieved from: https://www.kantar.com/inspiration/coronavirus/chinese-publics-health-awareness-and-behaviour-during-epidemic

Liu, K., & Tao, D. (2022). The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services. *Computers in Human Behavior*, *127*, 107026. https://doi.org/https://doi.org/10.1016/j.chb.2021.107026

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), 629-650.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *The Academy of Management Review*, *20*(3), 709-734.

Meyer, A. N., Giardina, T. D., Spitzmueller, C., Shahid, U., Scott, T. M., & Singh, H. (2020). Patient perspectives on the usefulness of an artificial intelligence–assisted symptom checker: Cross-sectional survey study. *Journal of Medical Internet Research*, *22*(1), e14679.

Miller, S., Gilbert, S., Virani, V., & Wicks, P. (2020). Patients' utilization and perception of an artificial intelligence–based symptom assessment and advice technology in a British primary care waiting room: Exploratory pilot study. *JMIR Human Factors*, *7*(3), e19713.

Min, J., & Kim, B. (2015). How are people enticed to disclose personal information despite privacy concerns in social network sites? The calculus between benefit and cost. *Journal of the Association for Information Science and Technology*, *66*(4), 839-857.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, *58*(3), 20-38. https://doi.org/10.2307/1252308

Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping

researchers discuss more sophisticated models. *Industrial Management & Data Systems*, *116*(9), 1164-1849.
Ostrom, A. L., Fotheringham, D., & Bitner, M. J. (2019). Customer acceptance of AI in service encounters: Understanding antecedents and consequences. In *Handbook of service science* (Vol. II). Springer.
Park, J., Amendah, E., Lee, Y., & Hyun, H. (2019). M-payment service: Interplay of perceived risk, benefit, and trust in service adoption. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *29*(1), 31-43. https://doi.org/https://doi.org/10.1002/hfm.20750
Phelps, J., Nowak, G., & Ferrell, E. (2000). Privacy concerns and consumer willingness to provide personal information. *Journal of Public Policy & Marketing*, *19*(1), 27-41.
Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management*, *12*(4), 531-544.
Powell, M., & Ansic, D. (1997). Gender differences in risk behaviour in financial decision-making: An experimental analysis. *Journal of Economic Psychology*, *18*(6), 605-628.
Princi, E., & Krämer, N. C. (2020). Out of control–privacy calculus and the effect of perceived control and moral considerations on the usage of IoT healthcare devices. *Frontiers in Psychology*, *11*, 582054.
Sarkar, S., Chauhan, S., & Khare, A. (2020). A meta-analysis of antecedents and consequences of trust in mobile commerce. *International Journal of Information Management*, *50*, 286-301.
Shareef, M. A., Kumar, V., Kumar, U., & Dwivedi, Y. K. (2011). e-Government Adoption Model (GAM): Differing service maturity levels. *Government Information Quarterly*, *28*(1), 17–35.
Shepherd, R. P. (2016). Men, women, and web 2.0 writing: Gender difference in Facebook composing. *Computers and Composition*, *39*, 14-26. https://doi.org/https://doi.org/10.1016/j.compcom.2015.11.002
Sia, C. L., Lim, K. H., Leung, K., Lee, M. K. O., Huang, W. W., & Benbasat, I. (2009). Web strategies to promote Internet shopping: Is cultural-customization needed? *MIS Quarterly*, *33*(3), 491-512. https://doi.org/10.2307/20650306
Sun, Y., Wang, N., & Shen, X.-L. (2021). Calculus interdependency, personality contingency, and causal asymmetry: Toward a configurational privacy calculus model of information disclosure. *Information & Management*, *58*(8), 103556. https://doi.org/https://doi.org/10.1016/j.im.2021.103556
Sun, Y., Wang, N., Shen, X.-L., & Zhang, J. X. (2015). Location information disclosure in location-based social network services: Privacy calculus, benefit structure, and gender differences. *Computers in Human Behavior*, *52*, 278-292. https://doi.org/https://doi.org/10.1016/j.chb.2015.06.006
Thelwall, M., & Vis, F. (2017). Gender and image sharing on Facebook, Twitter, Instagram, Snapchat and WhatsApp in the UK. *Aslib Journal of Information Management*, *69*(6), 702-720. https://doi.org/10.1108/AJIM-04-2017-0098
Tufekci, Z. (2007). Can you see me now? Audience and disclosure regulation in online social network sites. *Bulletin of Science, Technology & Society*, *28*(1), 20-36. https://doi.org/10.1177/0270467607311484
Venkatesh, V., Thong, J., & 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.
Verkijika, S. F. (2019). 'If you know what to do, will you take action to avoid mobile phishing attacks': Self-efficacy, anticipated regret, and gender. *Computers in Human Behavior*, *101*, 286-296.
Wang, E. S.-T., & Chou, N. P.-Y. (2014). Consumer characteristics, social influence, and system factors on online group-buying repurchasing intention. *Journal of Electronic Commerce Research*, *15*(2), 119-132.
Wang, L., Luo, X. R., & Yang, X. (2022). Carrot or stick? Exploring the effect of word-of-mouth on mobile payment application switching behaviors. *Journal of Electronic Commerce Research*, *23*(2), 77-98.
Wang, T., Duong, T. D., & Chen, C. C. (2016). Intention to disclose personal information via mobile applications: A privacy calculus perspective. *International Journal of Information Management*, *36*(4), 531-542. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2016.03.003
Wu, K.-W., Huang, S. Y., Yen, D. C., & Popova, I. (2012). The effect of online privacy policy on consumer privacy concern and trust. *Computers in Human Behavior*, *28*(3), 889-897.
Xiang, Y., Zhao, L., Liu, Z., Wu, X., Chen, J., Long, E., Lin, D., Zhu, Y., Chen, C., & Lin, Z. (2020). Implementation of artificial intelligence in medicine: Status analysis and development suggestions. *Artificial Intelligence in Medicine*, *102*, 101780. https://doi.org/10.1016/j.artmed.2019.101780
Xu, H., Luo, X. R., Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision making process for location-aware marketing. *Decision Support Systems*, *51*(1), 42-52.
Xu, H., Teo, H. H., Tan, B., & Agarwal, R. (2009). The role of push-pull technology in privacy calculus: The case of location-based services. *Journal of Management Information Systems*, *26*(3), 135-174.
Xu, H., Teo, H. H., Tan, B. C. Y., & Agarwal, R. (2012). Effects of individual self-protection, industry self-regulation, and government regulation on privacy concerns: A study of location-based services. *Information Systems*

Research, *23*(4), 1342-1363.

Yang, Q., Pang, C., Liu, L., Yen, D. C., & Tarn, J. M. (2015). Exploring consumer perceived risk and trust for online payments: An empirical study in China's younger generation. *Computers in Human Behavior*, *50*, 9-24.

You, Y., & Gui, X. (2020). Self-diagnosis through AI-enabled chatbot-based symptom checkers: User experiences and design considerations. In *AMIA Annual Symposium Proceedings* (p. 1354).

Yun, H., Han, D., & Lee, C. C. (2013). Understanding the use of location-based service applications: Do privacy concerns matter? *Journal of Electronic Commerce Research*, *14*(3), 215-230.

Zhang, C.-B., Li, Y.-N., Wu, B., & Li, D.-J. (2017). How WeChat can retain users: Roles of network externalities, social interaction ties, and perceived values in building continuance intention. *Computers in Human Behavior*, *69*, 284-293. https://doi.org/https://doi.org/10.1016/j.chb.2016.11.069

Zhang, K. Z. K., Cheung, C. M. K., & Lee, M. K. O. (2014). Examining the moderating effect of inconsistent reviews and its gender differences on consumers' online shopping decision. *International Journal of Information Management*, *34*(2), 89-98.

Zhang, L., Shao, Z., Li, X., & Feng, Y. (2021). Gamification and online impulse buying: The moderating effect of gender and age. *International Journal of Information Management*, *61*, 102267. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2020.102267

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 207-220.

Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management*, *43*, 342-350. https://doi.org/10.1016/j.ijinfomgt.2017.08.006

Zhou, Z., Jin, X. L., & Fang, Y. (2014). Moderating role of gender in the relationships between perceived benefits and satisfaction in social virtual world continuance. *Decision Support Systems*, *65*(1), 69-79. https://doi.org/http://dx.doi.org/10.1016/j.dss.2014.05.004

Zhu, H., Ou, C. X., van den Heuvel, W.-J. A., & Liu, H. (2017). Privacy calculus and its utility for personalization services in e-commerce: An analysis of consumer decision-making. *Information & Management*, *54*(4), 427-437.

Zhu, M., Wu, C., Huang, S., Zheng, K., Young, S. D., Yan, X., & Yuan, Q. (2021). Privacy paradox in mHealth applications: An integrated elaboration likelihood model incorporating privacy calculus and privacy fatigue. *Telematics and Informatics*, *61*, 101601.

Appendix A

The formula for testing the significance of differences in path coefficients is $S_{pooled} = \sqrt{\frac{N_1-1}{N_1+N_2-2} \times SE_1^2 + \frac{N_2-1}{N_1+N_2-2} \times SE_2^2}$, $t = \frac{PC_1-PC_2}{S_{pooled}\sqrt{\frac{1}{N_1}+\frac{1}{N_2}}}$, where S_{pooled} is the joint variance; t represents the statistical value of the degree of freedom ($N_1 + N_2 - 2$); Ni represents the ith sample's sample size; SEi represents the standard error of the path coefficient of the structural equation model for the ith sample; and PCi denotes the path coefficient of the structural equation model for the ith sample.