ABAC ODI JOURNAL Vision. Action. Outcome

ISSN: 2351-0617 (print), ISSN: 2408-2058 (electronic)

Assessing Adults' Privacy Risk, Attitude, and Behavioral Intention Toward Mobile Health Communities in Mianyang, China

Fengliang Chen, Qizhen Gu

ABAC ODI JOURNAL Vision. Action. Outcome Vol 13(3) pp. 190-209

https://assumptionjournal.au.edu/index.php/odijournal

Published by the
Organization Development Institute
Graduate School of Business and Advanced Technology Management
Assumption University Thailand

ABAC ODI JOURNAL Vision. Action. Outcome
is indexed by the Thai Citation Index and ASEAN Citation Index

Assessing Adults' Privacy Risk, Attitude, and Behavioral Intention Toward Mobile Health Communities in Mianyang, China

Fengliang Chen[1], Qizhen Gu[2]

[1]Ph.D. Candidate in Information Technology, Vincent Mary School of Engineering, Science and Technology, Assumption University of Thailand. Email: p6619212@au.edu
[2]Faculty Member, Graduate School of Business and Advanced Technology Management, Assumption University of Thailand. Email: guqizhen@au.edu

Received: 16 July 2025 . Revised: 24 August 2025. Accepted: 2 September 2025

Abstract

This study investigates the behavioral intention of adults in Mianyang, China, to use mobile health communities (MHCs). Drawing upon the Trust-Risk Framework, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and Social Cognitive Theory, a structural equation model was developed to examine how performance expectancy, trust, self-efficacy, privacy risk, social influence, and attitude influence user intention. A total of 450 valid questionnaires were collected from adult users in Mianyang, China, all of whom had prior experience using MHCs. Participants were recruited through a structured online survey. CFA was employed to verify construct validity, and SEM was used to test the model fit and hypothesized relationships. The findings reveal that attitude is the strongest predictor of behavioral intention, followed by trust and self-efficacy. Trust reduces perceived privacy risk and strengthens user attitude, forming a layered cognitive-affective pathway. Social influence shows a moderate yet significant effect, while performance expectancy exhibits limited impact—indicating that users prioritize emotional security and trust over functional efficiency in digital health settings. This research contributes to digital health adoption theory by contextualizing trust and risk in a high-sensitivity environment. It offers practical guidance for platform design, digital literacy training, and policy support aimed at improving user acceptance and sustained engagement.

Keywords: Mobile Health Communities, TAM, UTAUT, Behavioral Intention, Trust, Privacy Risk

Introduction

In recent years, mobile health technologies have become an integral component of digital healthcare ecosystems, offering scalable and user-centered solutions for chronic disease management, health monitoring, and patient engagement (Esmaeilzadeh & Elahi, 2021; Takao et al., 2012). Among these innovations, MHCs—interactive digital platforms enabling users to access health information, consult professionals, and share personal experiences—have gained increasing prominence, particularly in countries like China where healthcare demand is growing and resources remain unevenly distributed (Huajing Industrial Research Institute, 2023).

This growth coincides with a surge in chronic disease prevalence—accounting for 79.4% of total deaths in China—and demographic shifts such as population aging (Huajing Industrial Research Institute, 2023). The COVID-19 pandemic further catalyzed the use of MHCs by amplifying the need for accessible, contactless, and personalized digital health tools (Gopalsamy et al., 2017). During this period, MHCs provided crucial services ranging from online consultations to psychological support and chronic condition follow-up, thereby alleviating hospital congestion and expanding access for underserved groups (Goh et al., 2016; Yan & Tan, 2014). Despite this momentum, user adoption—especially among adults—remains fragmented. Technological readiness and policy endorsement have not fully translated into behavioral intention or long-term engagement.

Previous studies on digital health adoption have predominantly employed models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), focusing on perceived usefulness, ease of use, and social influence (Hesse et al., 2005; Venkatesh et al., 2003). While these models are foundational, they often overlook critical psychological and emotional factors relevant in health-related contexts. In high-sensitivity environments involving personal health data, users' trust, self-efficacy, and perceived privacy risks can be more decisive than functional perceptions alone (Esmaeilzadeh & Elahi, 2021; Nambisan, 2011).

Building on these insights, this study develops a multidimensional and context-sensitive adoption framework that integrates seven core constructs: performance expectancy, trust, self-efficacy, privacy risk, social influence, attitude, and behavioral intention. Drawing from TAM/UTAUT, trust theory, self-efficacy theory, and the Theory of Planned Behavior (TPB), this framework moves beyond single-theory approaches by capturing cognitive, affective, and social dimensions of user decision-making. Specifically, the model posits that trust reduces perceived privacy risks and fosters more positive attitudes, while self-efficacy enhances users' confidence and control, thereby facilitating adoption. These theoretical linkages align with a staged “cognition-affect-behavior” mechanism that better reflects user psychology in digital health settings.

A structured questionnaire was administered to 450 adult MHCs users in Mianyang, a digitally advanced yet unevenly adopting city in western China. SEM and CFA confirmed key

model pathways. Attitude was the strongest predictor of behavioral intention, followed by trust and self-efficacy. Trust directly influenced intention and indirectly shaped attitudes by reducing privacy concerns. Self-efficacy improved perceived control and lowered technical barriers. Social influence had a moderate but significant effect, while performance expectancy showed weak predictive power, revealing a gap between user expectations and perceived value.

These findings offer both theoretical and practical value. Theoretically, the study proposes an integrative framework suited to high-risk, health-focused digital contexts by embedding trust and privacy into traditional models. Practically, enhancing users' confidence and perceived value—through intuitive design, visual health tracking, and smart feedback—can boost engagement. Building trust via transparent policies, expert-backed content, and trial access (e.g., no-login mode) also shapes positive attitudes. At the policy level, promoting cross-institutional collaboration and digital literacy programs for vulnerable groups, such as the elderly, is key to equitable and sustained MHCs participation.

In summary, by combining theoretical depth with empirical rigor, this study offers a refined understanding of MHCs adoption in China's adult population. It provides a foundation for designing inclusive, trustworthy, and psychologically attuned mobile health ecosystems that support long-term behavioral engagement and contribute to public health goals.

Literature Review

Related Literature

Performance Expectancy

Performance Expectancy (PE) refers to the degree to which an individual believes that using a specific system will lead to performance gains (Venkatesh et al., 2003). Within mobile health contexts, PE reflects users' perceptions of how engaging with MHCs can enhance their self-management efficiency or improve health-related outcomes (Dwivedi et al., 2016). Empirical studies have consistently shown that PE is a critical determinant of users' technology adoption behavior. For instance, Wu et al. (2011) confirmed a positive relationship between PE and the intention to adopt mobile medical services. Ghalandari (2012) further emphasized that individuals are more inclined to use technology when they perceive it as offering clear, valuable benefits. In the context of ICT innovations, Williams et al. (2015) and Baishya and Samalia (2020) both reported a strong correlation between PE and Behavioral Intention (BI). Similarly, Thusi and Maduku (2020) found that PE significantly influenced mobile commerce adoption, while Hassaan et al. (2023) identified a comparable effect in the smart banking sector. Taken together, these findings suggest that when users perceive MHCs as beneficial to their health performance, they are more likely to develop adoption intentions.

Trust

Trust (T) refers to a user's belief in the reliability, honesty, and competence of a platform or service provider (Zaltman & Moorman, 1988). In MHCs, where users often share sensitive personal information, trust plays a crucial role in shaping their willingness to participate. It helps reduce concerns about data misuse and encourages engagement. Previous

studies have consistently found a negative relationship between trust and perceived privacy risk (Dinev & Hart, 2006a; Nemec Zlatolas et al., 2019, 2019; Pavlou & Gefen, 2004; Wang & Lin, 2016; Zhou, 2012). As trust increases, users tend to perceive less risk in disclosing personal information. Trust has also been shown to positively influence users' behavioral intentions across various digital services, including e-health, mobile banking, and online consultations (Akdur et al., 2020; Dash & Sahoo, 2022; Gefen, 2000). In MHCs, trust serves a dual function: it lowers perceived privacy risks and increases users' intention to use the platform.

Privacy Risk

Privacy Risk (PR) refers to the perceived likelihood that users' personal information may be accessed, misused, or shared without consent, particularly by marketers, third parties, or malicious actors. This concern is exacerbated in mobile health contexts due to the sensitive nature of health-related data. Lupton (2014) observed that users often hesitate to share detailed personal health information—such as diet, lifestyle, or medical history—due to fears of unauthorized access. Bansal et al. (2010) further underscored that privacy concerns significantly hinder technology acceptance in eHealth and mHealth environments. Sunyaev et al. (2015) analyzed 600 mHealth apps and discovered that fewer than one-third had any privacy policies, indicating widespread vulnerabilities. Additionally, Krebs and Duncan (2015) and Shareef et al. (2014) emphasized the necessity for regulatory oversight and ethical safeguards in mobile health systems. Research consistently demonstrates that privacy risk negatively impacts users' Behavioral Intention (BI), acting as a deterrent to technology adoption (Alqahtani & Orji, 2020; El-Wajeeh et al., 2014; Wei et al., 2021). Therefore, addressing privacy concerns is crucial for fostering user trust and facilitating the widespread use of MHCs.

Self-Efficacy

Self-Efficacy (SE) refers to an individual's belief in their ability to perform tasks (Rosenstock et al., 1988). In digital health, SE reflects users' confidence in navigating mobile health platforms. Prior research (Deng, 2013; Guo et al., 2015) shows higher SE leads to greater optimism and positive attitudes toward mobile health. SE enhances perceived competence, fostering trust and favorable emotional evaluations. Fishbein and Ajzen (1975) also confirmed SE strongly predicts positive health behaviors. Thus, improving SE is key to shaping positive attitudes toward MHCs.

Attitude

Attitude (ATT) refers to an individual's overall evaluative judgment—positive or negative—toward engaging with mobile health services (MHS). Grounded in the Theory of Planned Behavior (TPB), attitude has been widely recognized as a strong predictor of Behavioral Intention (BI) (Deng et al., 2014; Lee et al., 2011; I.-L. Wu et al., 2011). When users form favorable evaluations of MHS—perceiving it as useful, reliable, or supportive—they are more likely to express an intention to adopt these services. This relationship has also been validated across various domains, such as self-service technologies, cloud computing, and online banking (Al-Somali et al., 2009; Asadi et al., 2017; L. Chen & Wu, 2014). Zhao et al. (2018) further confirmed that attitude exhibits the strongest correlation with BI among mobile healthcare users. In hospitality and retail contexts, studies by Boo and Chua (2022) and Ki and

Hon (2012) have also observed that positive attitudes toward technology or organizations significantly shape behavioral engagement. Therefore, enhancing users' attitudes toward MHS—by improving perceived value and emotional acceptance—is critical for encouraging adoption.

Social Influence

Social Influence (SI) refers to the perceived pressure from significant others—such as peers, family, or professionals—to adopt a technology (Lee et al., 2011). Based on the UTAUT model, SI involves learning by observing social circles before adoption decisions. Numerous studies confirm SI's significant role in shaping Behavioral Intention (BI) in mobile contexts. For instance, SI positively impacts adoption in mobile commerce (Alalwan et al., 2017; Farah et al., 2018) and mobile banking (Tan & Leby Lau, 2016; Tarhini et al., 2016). In mobile health, SI influences older adults' willingness to use services (Pan & Jordan-Marsh, 2010; Sun et al., 2013) and similar effects appear in Bangladesh (Quaosar et al., 2018) and education (Kim & Lee, 2022). Thus, peer approval and modeling enhance MHCs adoption.

Behavioral Intention

Behavioral Intention (BI) refers to an individual's conscious willingness or plan to engage in a specific behavior (Fishbein & Ajzen, 1975). In the context of technology adoption, BI serves as a proximal predictor of actual usage behavior, often mediating the relationship between attitudinal, cognitive, and contextual factors and system use (Davis, 1989; Venkatesh et al., 2003, 2012). Within e-health settings, BI is pertinent not only for patients but also for healthcare providers. Chen et al. (2020) found that physicians with a positive attitude toward digital consulting services are more likely to exhibit a stronger behavioral intention to adopt such tools. Similarly, Kaplanidou et al. (2013) conceptualized BI as the psychological commitment that precedes actual action. In self-service technology (SST) contexts, BI often manifests as users' readiness to continuously engage with digital tools (Manrai et al., 2021). Studies by Alam et al. (2020) and Chang et al. (2021) emphasized that BI significantly predicts users' ongoing use of digital products or services, making it a crucial construct for understanding sustained adoption behavior across various information system environments.

Hypotheses

This study develops a set of hypotheses centered on four key psychological constructs—privacy risk, attitude, and behavioral intention—to systematically explore how these factors jointly influence users' intention to engage with MHCs. By empirically testing these hypotheses (see Figure 1), the study aims to offer targeted recommendations for platform providers to enhance privacy protection, foster user trust, improve user attitudes, and ultimately increase behavioral intention to use MHCs services.

Hypothesis 1 (H1): performance expectancy has significant impact on behavioral intention.

Hypothesis 2 (H2): trust has significant impact on privacy risk.

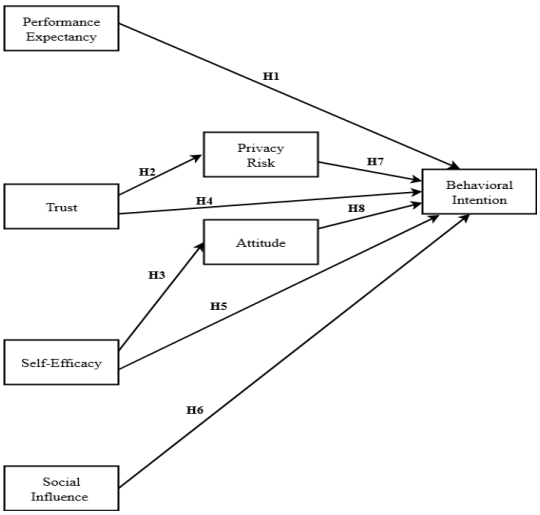
Hypothesis 3 (H3): self-efficacy has significant impact on attitude.

Hypothesis 4 (H4): trust has significant impact on behavioral intention.

Hypothesis 5 (H5): self-efficacy has significant impact on behavioral intention.
Hypothesis 6 (H6): social Influence has significant impact on behavioral intention.
Hypothesis 7 (H7): privacy risk has significant impact on behavioral intention.
Hypothesis 8 (H8): attitude has significant impact on behavioral intention.

Figure 1

Research Framework "Assessing Adults' Privacy Risk, Attitude, and Behavioral Intention Toward Mobile Health Communities in Mianyang, China"



Note: Created by the author

Research Methodology

The study adopts a quantitative research methodology to examine the relationships among PE (Performance Expectancy), T (Trust), SE (Self-Efficacy), SI (Social Influence), PR (Privacy Risk), ATT (Attitude), and BI (Behavioral Intention) in the MHCs context. The methodology includes research design, sampling procedures, and data analysis strategies.

Research Design

This study adopts a quantitative, cross-sectional design to examine factors influencing PR, ATT, and BI among adults using MHCs in Mianyang, China. Based on TRA, TAM, UTAUT, PMT, and TPB, the framework includes PE, T, SE, SI, PR, ATT, and BI. Data were collected via structured questionnaires from chronic disease patients in four public hospitals using multistage sampling. A total of 450 responses were targeted, following SEM sample size guidelines. All constructs were measured with validated Likert-scale items. Data analysis involved CFA and SEM using SPSS and AMOS to test the reliability, validity, and hypothesized relationships among the variables.

Population and Sample

This study focuses on adult patients with chronic conditions in Mianyang, China, who are familiar with their medical history and have used MHCs. To ensure representativeness and minimize sampling bias, a non-probability quota sampling method was primarily adopted. Participants were recruited from the cardiology and endocrinology departments of four public hospitals: Mianyang Central Hospital, the Third Hospital of Mianyang, Mianyang Hospital of Traditional Chinese Medicine, and Mianyang People's Hospital. Based on the total departmental population (N = 8,944), proportional allocation was applied following Cochran's formula and SEM sample size guidelines.

This study used a multi-stage sampling approach combining purposive, quota and convenience sampling methods. First, four public hospitals in Mianyang were selected in a rigorous manner on the basis of the number of patients and the medical records system. Second, proportional quota sampling was used to distribute the questionnaires to the hospitals according to their patient population (8,944 patients in total) in the cardiovascular and endocrinology wards. Finally, in order to recruit patients who met the inclusion criteria, convenience sampling was used in each ward. The final sample consisted of 143, 75, 122 and 110 participants from the central Mianyang hospital, third hospital, T.C.M. hospital and People's Hospital, respectively.

Data collection took place between August and October of the year 2024 using online surveys, A total of 450 valid responses was obtained and used for analysis. Table 1 presents the stratified sample allocation across the four hospitals. Patients were selected based on predefined inclusion criteria and invited to complete structured questionnaires distributed through both online and offline channels.

Table 1

Sample Unit and Sample Size

Major Name	Population Size	Proportional Sample Size
Mianyang Central Hospital patients	2583	143
The Third Hospital of Mianyang patients	1964	75
Mianyang Hospital of T.C.M patients	2675	122
Mianyang People's Hospital patients	1722	110
Total	8944	450

Note: Created by the author

Data Analysis Methods

Data were analyzed using SPSS and AMOS. Descriptive statistics summarized demographics and construct means. Reliability and content validity were assessed via Cronbach's Alpha and IOC. CFA confirmed construct validity and model fit. SEM tested hypothesized paths among PE, T, SE, SI, PR, ATT, and BI, including mediation by PR and ATT.

Data screening and standard fit indices ensured model adequacy.

Results and Discussion

Demographic Information

As shown in Table 2, gender distribution is nearly equal (49.8% male, 50.2% female). Most respondents are over 36 years old (66.44%), with 32.66% aged 36-50 and 33.78% above 50. Regarding education, 51.11% hold a bachelor's degree, 21.56% master's or higher. In terms of income, 50.20% earn CNY 30,000-69,999, 22.22% below CNY 30,000, and 10% above CNY 90,000.

Table 2

Demographic Information

Demographic Information (N=450)		**Frequency**	**Percentage**
Gender	Male	224	49.80%
	Female	226	50.20%
Age	18-25 years old	44	9.78%
	26-35 years old	107	23.78%
	36-50 years old	147	32.66%
	>50 years old	152	33.78%
Education Level	Elementary/ Middle/ High School	41	9.11%
	Associate degree	82	18.22%
	Bachelor`s degree	230	51.11%
	Master`s degree or higher	97	21.56%
Annual Income	< CNY 30,000	100	22.22%
	CNY 30,000-49,999	113	25.10%
	CNY 50,000-69,999	113	25.10%
	CNY 70,000-89,999	79	17.56%
	>CNY 90,000	45	10.00%

Note: Created by the author

Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) confirmed the measurement model's reliability and validity (see Table 3). All factor loadings exceeded 0.60. Cronbach's Alpha and Composite Reliability (CR) values ranged from 0.731 to 0.826. Although some AVEs (e.g., ATT, SE, SI) were slightly below 0.50, all CRs were above 0.70, satisfying Fornell and Larcker's (1981) criterion. This approach is in line with established practice where convergent validity is considered acceptable with CR > 0.70 and AVE values slightly less than 0.50 (Kyriazos et al., 2018; Shaakumeni & Csapo, 2019). Malhotra (2020) also claimed that the criteria for the AVE are often too stringent and that their validity can only be determined by CR. These results indicate acceptable convergent validity and support the model's use in subsequent analysis.

Table 3

Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Items Amount	Factor Loading	Cronbach's Alpha	CR	AVE
PE	4	0.690~0.746	0.800	0.801	0.501
T	4	0.697~0.806	0.825	0.826	0.543
PR	4	0.705~0.799	0.824	0.825	0.541
SE	3	0.678~0.730	0.748	0.748	0.497
ATT	3	0.660~0.707	0.731	0.731	0.476
SI	4	0.614~0.747	0.769	0.772	0.460
BI	4	0.716~0.746	0.823	0.823	0.538

Note: Created by the author

As shown in Table 4, the square roots of AVE (diagonal values) for each latent construct are greater than their corresponding inter-construct correlations (off-diagonal values). This satisfies the Fornell-Larcker criterion, indicating that all constructs demonstrate adequate discriminant validity. Therefore, each construct in the measurement model captures unique variance and is empirically distinct from others.

Table 4

Discriminant Validity

	PE	T	PR	SE	ATT	SI	BI
PE	0.708						
T	0.353	0.737					
PR	-0.282	-0.447	0.736				
SE	0.388	0.400	-0.238	0.705			
ATT	0.396	0.363	-0.327	0.366	0.690		
SI	0.365	0.387	-0.352	0.441	0.439	0.678	
BI	0.339	0.392	-0.372	0.360	0.439	0.405	0.733

Note: Created by the author

Structural Equation Model (SEM)

Structural Equation Modeling (SEM) was conducted to test the hypothesized relationships among PE, T, SE, SI, PR, ATT, and BI. Following the guidelines of Kline (2015), SEM integrates confirmatory factor analysis and path analysis, allowing simultaneous estimation of multiple structural paths while accounting for measurement error.

As shown in Table 5, model fit improved after adjustment. The CMIN/df decreased from 3.226 to 3.592, meeting the acceptable threshold of <5 (Al-Mamary et al., 2015; Awang, 2012). The GFI increased from 0.838 to 0.853, exceeding the minimum criterion of 0.85, while AGFI improved from 0.804 to 0.819, surpassing the 0.80 cutoff (Sica & Ghisi, 2007).

Incremental fit indices also indicated improvement: NFI rose from 0.782 to 0.808 (Wu & Wang, 2006), CFI from 0.831 to 0.858 (Bentler, 1990), and TLI from 0.812 to 0.838 (Sharma et al., 2005). The RMSEA value declined from 0.076 to 0.070, falling well within the acceptable range of <0.08 (Pedroso et al., 2016). Together, these improved indices confirm that the revised model provides an acceptable fit and better captures the structural relationships among the key constructs.

Table 5

Goodness of Fit for Structural Model

Index	Criterion	Before Adjustment Statistical Values	After Adjustment Statistical Values
CMIN/df	<5 (Al-Mamary et al., 2015; Awang, 2012)	3.592	3.226
GFI	≥0.85 (Sica & Ghisi, 2007)	0.838	0.853
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.804	0.819
CFI	≥0.80 (Bentler, 1990)	0.831	0.858
NFI	≥0.80 (Wu & Wang, 2006)	0.782	0.808
TLI	≥0.80 (Sharma et al., 2005)	0.812	0.838
RMSEA	<0.08 (Pedroso et al., 2016)	0.076	0.070
Model Summary		Unacceptable Model Fit	Acceptable Model Fit

Note: Created by the author

Hypothesis Testing Results

Structural Equation Modeling (SEM) was used to test the hypothesized relationships among PE, T, SE, SI, PR, ATT, and BI. As shown in Table 6, all eight hypotheses were supported with statistically significant path coefficients ($p < 0.05$), confirming the model's structural validity (Kline, 2015).

H1 posits that PE positively influences BI. The result ($\beta = 0.111$, $t = 2.263$, $p < 0.05$) supports the hypothesis, indicating that higher PE modestly enhances intention to use MHCs. H2 examines the effect of T on PR. A strong negative relationship is confirmed ($\beta = -0.575$, $t = -8.658$, $p < 0.001$), suggesting that higher trust reduces perceived privacy risk, consistent with prior findings (Dinev & Hart, 2006b; Pavlou & Gefen, 2004).

H3 tests the impact of SE on ATT. The significant coefficient ($\beta = 0.511$, $t = 6.729$, $p < 0.001$) supports the idea that greater self-efficacy leads to more positive user attitudes.

H4 and H5 evaluate the direct effects of T and SE on BI, with both showing significant positive effects (H4: $\beta = 0.121$, $t = 1.997$, $p < 0.05$; H5: $\beta = 0.137$, $t = 1.983$, $p < 0.05$). H6 confirms that SI positively influences BI ($\beta = 0.175$, $t = 3.005$, $p < 0.05$), implying that social influence plays a notable role in users' intention to adopt MHCs. H7 assesses the effect of PR on BI. The negative path coefficient ($\beta = -0.178$, $t = -3.039$, $p < 0.05$) supports the notion that higher privacy concerns discourage behavioral intention. Finally, H8 confirms a strong

positive link between ATT and BI (β = 0.266, t = 3.870, p < 0.001), reinforcing the role of attitude as a key determinant of usage intention.

Table 6

Hypothesis Results of the Structural Equation Modeling

Hypothesis	Paths	Standardized Path Coefficient (β)	t-Value	Testing Result
H1	PE → BI	0.111	2.263*	Supported
H2	T → PR	-0.575	-8.658***	Supported
H3	SE → ATT	0.511	6.729***	Supported
H4	T → BI	0.121	1.997*	Supported
H5	SE → BI	0.137	1.983*	Supported
H6	SI → BI	0.175	3.005*	Supported
H7	PR → BI	-0.178	-3.039*	Supported
H8	ATT → BI	0.266	3.87***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
Note: Created by the author

Discussion

H1: The results show that PE has a positive but modest effect on BI, with a standardized path coefficient of 0.111. This suggests that when users believe MHCs are useful for managing their health, their behavioral intention increases. Similar conclusions were drawn by Aydin (2023), who found performance expectancy to be a meaningful predictor of mobile health adoption.

H2: The analysis confirms a strong negative association between T and PR (β = -0.575), indicating that greater trust significantly reduces users' privacy risk. This aligns with Pavlou and Gefen (2004), who emphasized the inverse relationship between trust and privacy concern in online systems.

H3: SE significantly impacts ATT (β = 0.511), showing that users with higher self-confidence in managing digital platforms tend to hold more favorable attitudes toward MHCs. This finding supports the results of Zhang et al. (2019), who noted that self-efficacy enhances users' receptiveness to health technologies.

H4: T directly influences BI (β = 0.121), confirming that user trust contributes not only to reduced privacy risk but also enhances usage intention. This dual role of trust is consistent with findings by Akdur et al. (2020).

H5: SE also has a direct positive effect on BI (β = 0.137), indicating that confident users are more likely to engage with MHCs. Alam et al. (2020) similarly found that SE drives both ATT and BI in mobile health adoption.

H6: SI exerts a moderate influence on BI (β = 0.175), implying that social cues and peer encouragement play a role in motivating users to engage with MHCs. This supports previous work on technology diffusion, including Venkatesh et al. (2003).

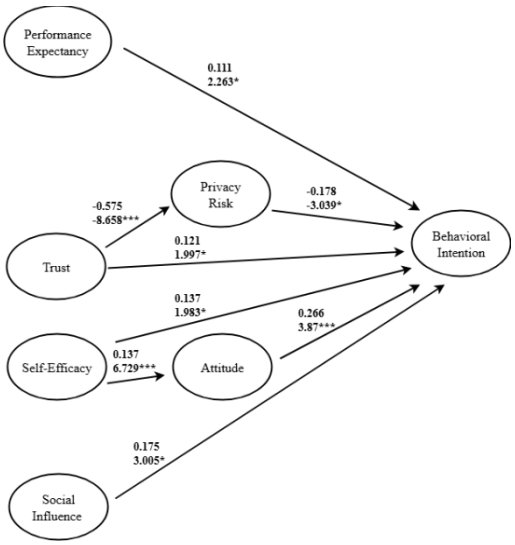
H7: PR negatively affects BI (β = -0.178), indicating that privacy concerns remain a barrier to technology use. This is consistent with findings from Wang and Lin (2016) and Nemec Zlatolas et al. (2019), who observed that perceived risk often inhibits digital disclosure behavior.

H8: ATT has a substantial positive effect on BI (β = 0.266), making it the strongest direct predictor of behavioral intention in this model. This validates previous claims (Boo & Chua, 2022) that user attitude is central to the acceptance of mobile health technologies.

Figure 2 illustrates the structural model with four independent variables (PE, T, SE, SI), two mediators (PR, ATT), and one dependent variable (BI). The model explains 29.2% of the variance in PR, 23.2% in ATT, and 26.9% in BI. ATT shows the strongest positive effect on BI (β = 0.266, p < 0.001), followed by SI (β = 0.175), SE (β = 0.137), T (β = 0.121), and PE (β = 0.111), all significant at p < 0.05. PR negatively affects BI (β = -0.178, p < 0.05), indicating that privacy concerns reduce usage intention. As mediators, ATT is positively influenced by SE (β = 0.511, p < 0.001) and PE (β = 0.111, p < 0.05), while PR is significantly reduced by T (β = -0.575, p < 0.001), highlighting trust's role in mitigating privacy concerns.

Figure 2

Path Diagram Analysis



Note: *** p<0.001, ** p<0.01, * p<0.05
Note: Created by the author

Conclusions and Recommendations

Conclusions

This study analyzes factors influencing BI to use MHCs among adults in Mianyang, China. The research tests seven hypotheses involving PE, T, SE, PR, SI, ATT, and BI. Data from 450 valid questionnaires were analyzed using CFA and SEM to validate the conceptual model.

Results show ATT is the strongest positive predictor of BI, followed by SI, SE, T, and PE. PR negatively affects BI, highlighting privacy concerns' impact on adoption. SE and PE significantly influence ATT, which mediates their effects on BI. T significantly reduces PR, confirming its role in alleviating privacy risk and indirectly promoting BI.

These findings deepen understanding of digital health acceptance, showing cognitive and affective factors' multiple pathways shaping BI. The rigorous methodology and robust sample enhance the study's relevance. This research offers empirical support for platform design and policy to improve user trust and engagement.

Recommendations

This study offers several practical insights for enhancing the adoption of MHCs across varied technological and user contexts.

1. Tailor platform functions to user familiarity and task complexity. In view of the significant impact of SE on ATT ($\beta = 0.511$) and BI ($\beta = 0.137$), and the specific measure of learning to use the mobile health community easily for me, and I can use the mobile health community easily for me, Developers should simplify interaction interfaces and optimize core features to meet the needs of users with differing levels of digital literacy. For example, using intuitive navigation, visual cues, and guided tutorials may improve usability and encourage adoption among first-time users.

2. Build trust mechanisms to alleviate perceived privacy risks. The strong negative correlation between T and PR ($\beta = -0.575$, $p<0.001$) suggests that the specific concerns measured in the survey should be addressed by building trust: ensuring that the mobile health community does not disclose personal data without permission to others, and that the professionals who have access to the information are properly managed. Introducing transparent data policies, visual consent mechanisms, and customizable privacy settings can reduce users' concerns. Regular third-party audits and certifications may also enhance platform credibility.

3. Segment users and personalize engagement strategies. Because ATT is the best predictor of BI ($\beta = 0.266$, $p<0.001$) and our focus of responses is on the good idea of using a mobile health community and on helping me manage my health more actively, Future implementations should distinguish between user groups such as general adults, elderly individuals, healthcare professionals, and corporate users. Tailoring communication and support services to different groups' motivations—such as health tracking, mandatory use, or clinical coordination—can boost engagement.

4. Invest in digital literacy training. Public health campaigns and institutional onboarding sessions can empower users with the skills needed to interact confidently with mobile health technologies, especially in regions with limited prior exposure to digital health tools.

5. Differentiate platform types in future development. Since user concerns may vary depending on platform tasks (e.g., community engagement vs. teleconsultation), it is advisable to classify and design platforms according to use-case specificity, ensuring that privacy and trust measures are context-appropriate.

6. Encourage comparative studies and cross-regional validations. To strengthen the generalizability of the current model, future research should test its robustness across diverse technological ecosystems and sociocultural environments, including longitudinal analysis to capture evolving user behavior.

Limitations and Further Exploration

This study has established a comprehensive theoretical model and tested key relationships among variables related to MHCs adoption. However, certain limitations warrant attention. First, the sample focused on general adult users without covering specific subpopulations such as elderly individuals or patients with chronic diseases, who may exhibit different digital health behaviors and perceptions. Second, data were collected within a limited geographic region and timeframe, which may restrict the generalizability of findings. Third, the model currently lacks emotional and contextual moderators that could enrich understanding of user behavior dynamics.

Future research should address these gaps by including more diverse user groups and expanding geographic and temporal scopes. Incorporating emotional factors such as privacy fatigue and external support as moderating variables can provide a more nuanced explanation of behavioral intentions. Additionally, longitudinal and mixed-methods approaches, combining behavioral data and self-reports, are recommended to enhance model robustness. Cross-regional validation studies will be critical to adapting the model to evolving digital health landscapes and varied user needs.

References

Akdur, G., Aydin, M. N., & Akdur, G. (2020). Adoption of mobile health apps in dietetic practice: Case study of Diyetkolik (Preprint). *JMIR mHealth and uHealth*, *8*(10). https://doi.org/10.2196/preprints.16911

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99-110.

Alam, M. Z., Hu, W., Hoque, M. R., & Kaium, M. A. (2020). Adoption intention and usage behavior of mHealth services in Bangladesh and China: A cross-country analysis. *International Journal of Pharmaceutical and Healthcare Marketing*, *14*(1), 37-60. https://doi.org/10.1108/IJPHM-03-2019-0023

Al-Mamary, Y. H., Shamsuddin, A., & Abdul Hamid, N. A. (2015). *Adoption of Management Information Systems in Context of Yemeni Organizations: A Structural*. *13*(6).

Alqahtani, F., & Orji, R. (2020). Insights from user reviews to improve mental health apps. *Health Informatics Journal*, *26*(3), 2042-2066.

Al-Somali, S. A., Gholami, R., & Clegg, B. (2009). An investigation into the acceptance of online banking in Saudi Arabia. *Technovation*, *29*(2), 130-141.

Asadi, S., Nilashi, M., Husin, A. R. C., & Yadegaridehkordi, E. (2017). Customers perspectives on adoption of cloud computing in banking sector. *Information Technology and Management*, *18*(4), 305-330. https://doi.org/10.1007/s10799-016-0270-8

Awang, Z. (2012). *Structural Equation Modeling (SEM) using AMOS Graphic* (5th ed.). Universiti Teknologi MARA Kelantan.

Aydin, G. (2023). Increasing mobile health application usage among Generation Z members: Evidence from the UTAUT model. *International Journal of Pharmaceutical and Healthcare Marketing*, *17*(3), 353-379. https://doi.org/10.1108/IJPHM-02-2021-0030

Baishya, K., & Samalia, H. V. (2020). Extending unified theory of acceptance and use of technology with perceived monetary value for smartphone adoption at the bottom of the pyramid. *International Journal of Information Management*, *51*, 102036. https://doi.org/10.1016/j.ijinfomgt.2019.11.004

Bansal, G., Zahedi, F. M., & Gefen, D. (2010). The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online. *Decision Support Systems*, *49*(2), 138-150.

Bentler, P. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238-246.

Boo, H. C., & Chua, B.-L. (2022). An integrative model of facial recognition check-in technology adoption intention: The perspective of hotel guests in Singapore. *International Journal of Contemporary Hospitality Management*, *34*(11), 4052-4079. https://doi.org/10.1108/IJCHM-12-2021-1471

Chang, Y.-T., Chao, C.-M., Yu, C.-W., & Lin, F.-C. (2021). Extending the Utility of UTAUT2 for hospital patients' adoption of medical apps: Moderating effects of e-health literacy. *Mobile Information Systems*, *2021*, 1-10. https://doi.org/10.1155/2021/8882317

Chen, L. S.-L., & Wu, K. I.-F. (2014). Antecedents of intention to use CUSS system: Moderating effects of self-efficacy. *Service Business*, *8*(4), 615-634.

Chen, Q., Yuan, Y., Feng, Y., & Archer, N. (2020). A decision paradox: Benefit vs risk and trust vs distrust for online dating adoption vs non-adoption. *Internet Research*, *31*(1), 341-375. https://doi.org/10.1108/INTR-07-2019-0304

Dash, A., & Sahoo, A. K. (2022). Exploring patient's intention towards e-health consultation using an extended UTAUT model. *Journal of Enabling Technologies*, *16*(4), 266-279. https://doi.org/10.1108/JET-08-2021-0042

Davis, F. D. (1989). Perceived Usefulness, Perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

Deng, Z. (2013). Understanding public users' adoption of mobile health service. *International Journal of Mobile Communications*, *11*(4), 351.

Deng, Z., Mo, X., & Liu, S. (2014). Comparison of the middle-aged and older users' adoption of mobile health services in China. *International Journal of Medical Informatics*, *83*(3), 210-224. https://doi.org/10.1016/j.ijmedinf.2013.12.002

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

Dwivedi, Y. K., Shareef, M. A., Simintiras, A. C., Lal, B., & Weerakkody, V. (2016). A generalised adoption model for services: A cross-country comparison of mobile health (m-health). *Government Information Quarterly*, *33*(1), 174-187.

El-Wajeeh, M., Galal-Edeen, G. H., & Mokhtar, H. (2014). Technology Acceptance Model for mobile health systems. *IOSR Journal of Mobile Computing & Application*, *1*(1), 21-33. https://doi.org/10.9790/0050-0112133

Esmaeilzadeh, A., & Elahi, R. (2021). Immunobiology and immunotherapy of COVID-19: A clinically updated overview. *Journal of Cellular Physiology*, *236*(4), 2519-2543. https://doi.org/10.1002/jcp.30076

Farah, M. F., Hasni, M. J. S., & Abbas, A. K. (2018). Mobile-banking adoption: Empirical evidence from the banking sector in Pakistan. *International Journal of Bank Marketing*, *36*(7), 1386-1413. https://doi.org/10.1108/IJBM-10-2017-0215

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

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*.

Gefen, D. (2000). E-commerce: The role of familiarity and trust. *Omega*, *28*(6), 725-737. https://doi.org/10.1016/S0305-0483(00)00021-9

Ghalandari, K. (2012). The effect of performance expectancy, effort expectancy, social influence and facilitating conditions on acceptance of e-banking services in Iran: The moderating role of age and gender. *Middle-East Journal of Scientific Research*, *12*(6), 801-807.

Goh, J. M., Gao, G., & Agarwal, R. (2016). The creation of social value: Can an online health community reduce rural-urban health disparities? *MIS Quarterly*, *40*(1), 247-263.

Gopalsamy, R., Semenov, A., Pasiliao, E., McIntosh, S., & Nikolaev, A. (2017). Engagement as a Driver of growth of online health forums: Observational study. *Journal of Medical Internet Research*, *19*(8), e304. https://doi.org/10.2196/jmir.7249

Guo, X., Han, X., Zhang, X., Dang, Y., & Chen, C. (2015). Investigating m-health acceptance from a protection motivation theory perspective: Gender and age differences. *Telemedicine and E-Health*, *21*(8), 661-669. https://doi.org/10.1089/tmj.2014.0166

Hassaan, M., Li, G., & Yaseen, A. (2023). Toward an understanding of Pakistani customers' adoption of smart banking services: An extended application of UTAUT2 model with big brother effect and information privacy concern. *International Journal of Bank Marketing*, *41*(7), 1715-1742. https://doi.org/10.1108/IJBM-09-2022-0396

Hesse, B. W., Nelson, D. E., Kreps, G. L., Croyle, R. T., Arora, N. K., Rimer, B. K., & Viswanath, K. (2005). Trust and sources of health information: the impact of the internet and its implications for health care providers: Findings from the first health information national trends survey. *Archives of Internal Medicine*, *165*(22), 2618. https://doi.org/10.1001/archinte.165.22.2618

Huajing Industrial Research Institute. (2023, June). *2023 China digital chronic disease management industry in-depth research report*. https://www.sohu.com/a/684653359_120113054

Kaplanidou, K. (Kiki), Karadakis, K., Gibson, H., Thapa, B., Walker, M., Geldenhuys, S., & Coetzee, W. (2013). Quality of life, event impacts, and mega-event support among South African Residents before and after the 2010 FIFA World Cup. *Journal of Travel Research*, *52*(5), 631-645. https://doi.org/10.1177/0047287513478501

Ki, E., & Hon, L. C. (2012). Causal linkages among relationship quality perception, attitude, and behavior intention in a membership organization. *Corporate Communications: An International Journal*, *17*(2), 187-208. https://doi.org/10.1108/13563281211220274

Kim, J., & Lee, K. S.-S. (2022). Conceptual model to predict Filipino teachers' adoption of ICT-based instruction in class: Using the UTAUT model. *Asia Pacific Journal of Education*, *42*(4), 699-713.

Kline, R. B. (2015). *Principles and Practice of Structural Equation Modeling*. Guilford Publications.

Krebs, P., & Duncan, D. T. (2015). Health app use among us mobile phone owners: A national survey. *JMIR mHealth and uHealth*, *3*(4), e101.

Kyriazos, T. A., Stalikas, A., Prassa, K., Galanakis, M., Yotsidi, V., & Lakioti, A. (2018). Psychometric evidence of the Brief Resilience Scale (BRS) and modeling distinctiveness of resilience from depression and stress. *Psychology*, *9*(7), 1828-1857. https://doi.org/10.4236/psych.2018.97107

Lee, M. K. O., Shi, N., Cheung, C. M. K., Lim, K. H., & Sia, C. L. (2011). Consumer's decision to shop online: The moderating role of positive informational social influence. *Information & Management*, *48*(6), 185-191.

Lupton, D. (2014). Apps as Artefacts: Towards a critical perspective on mobile health and medical apps. *Societies*, *4*(4), 606-622. https://doi.org/10.3390/soc4040606

Malhotra, N. K. (2020). Marketing research: An applied orientation. *Journal of Marketing Research*, *31*(1), 137. https://doi.org/10.2307/3151953

Manrai, R., Goel, U., & Yadav, P. D. (2021). Factors affecting adoption of digital payments by semi-rural Indian women: Extension of UTAUT-2 with self-determination theory and perceived credibility. *Aslib Journal of Information Management*, *73*(6), 814-838. https://doi.org/10.1108/AJIM-12-2020-0396

Nambisan, P. (2011). Information seeking and social support in online health communities: Impact on patients' perceived empathy. *Journal of the American Medical Informatics Association*, *18*(3), 298-304. https://doi.org/10.1136/amiajnl-2010-000058

Nemec Zlatolas, L., Welzer, T., Hölbl, M., Heriˇcko, M., & Kamišali´, A. (2019). A model of perception of privacy, trust, and self-disclosure on online social networks. *Entropy*, *21*(8), 772. https://doi.org/10.3390/e21080772

Pan, S., & Jordan-Marsh, M. (2010). Internet use intention and adoption among Chinese older adults: From the expanded technology acceptance model perspective. *Computers in Human Behavior*, *26*(5), 1111-1119. https://doi.org/10.1016/j.chb.2010.03.015

Pavlou, P. A., & Gefen, D. (2004). Building Effective Online marketplaces with institution-based trust. *Information Systems Research*, *15*(1), 37-59.

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry (São Paulo)*, *43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Quaosar, G. M. A. A., Hoque, R., & Bao, Y. (2018). Investigating factors affecting elderly's intention to use m-health services: An empirical study. *Telemedicine and E-Health*, *24*(4), 309-314. https://doi.org/10.1089/tmj.2017.0111

Rosenstock, I. M., Strecher, V. J., & Becker, M. H. (1988). Social learning theory and the health belief model. *Health Education Quarterly*, *15*(2), 175-183.

Shaakumeni, S. N., & Csapo, B. (2019). Exploring the factorial validity of the beliefs about nature of science questionnaire. *Science Education International*, *30*(1), 38-44. https://doi.org/10.33828/sei.v30.i1.5

Shareef, M. A., Kumar, V., & Kumar, U. (2014). Predicting mobile health adoption behaviour: A demand side perspective. *Journal of Customer Behaviour*, *13*(3), 187-205. https://doi.org/10.1362/147539214X14103453768697

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research*, *58*(7), 935-943. https://doi.org/10.1016/j.jbusres.2003.10.007

Sica, C., & Ghisi, M. (2007). *The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power*. Nova Science Publishers.

Sun, Y., Wang, N., Guo, X., & Peng, Z. (2013). Understanding the acceptance of mobile health services: A comparison and integration of alternative models. *Journal of Electronic Commerce Research*, *14*(2), 183-200.

Sunyaev, A., Dehling, T., Taylor, P. L., & Mandl, K. D. (2015). Availability and quality of mobile health app privacy policies. *Journal of the American Medical Informatics Association*, *22*(1), 28-33. https://doi.org/10.1136/amiajnl-2013-002605

Takao, H., Murayama, Y., Ishibashi, T., Karagiozov, K. L., & Abe, T. (2012). A new support system using a mobile device (smartphone) for diagnostic image display and treatment of stroke. *Stroke*, *43*(1), 236-239.

Tan, E., & Leby Lau, J. (2016). Behavioural intention to adopt mobile banking among the millennial generation. *Young Consumers*, *17*(1), 18-31. https://doi.org/10.1108/YC-07-2015-00537

Tarhini, A., El-Masri, M., Ali, M., & Serrano, A. (2016). Extending the UTAUT model to understand the customers' acceptance and use of internet banking in Lebanon: A structural equation modeling approach. *Information Technology & People*, *29*(4), 830-849. https://doi.org/10.1108/ITP-02-2014-0034

Thusi, P., & Maduku, D. K. (2020). South African millennials' acceptance and use of retail mobile banking apps: An integrated perspective. *Computers in Human Behavior*, *111*, 106405. https://doi.org/10.1016/j.chb.2020.106405

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

Venkatesh, V., Thong, J. Y. L., & 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. https://doi.org/10.2307/41410412

Wang, E. S.-T., & Lin, R.-L. (2016). Perceived quality factors of location-based apps on trust, perceived privacy risk, and continuous usage intention. *Behaviour & Information Technology*, 1-9. https://doi.org/10.1080/0144929X.2016.1143033

Wei, J., Vinnikova, A., Lu, L., & Xu, J. (2021). Understanding and predicting the adoption of fitness mobile apps: Evidence from China. *Health Communication*, *36*(8), 950-961.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, *28*(3), 443-488. https://doi.org/10.1108/JEIM-09-2014-0088

Wu, I. L., Li, J. Y., & Fu, C. Y. (2011). The adoption of mobile healthcare by hospital's professionals: An integrative perspective. *Decision Support Systems*, *51*(3), 587-596. https://doi.org/10.1016/j.dss.2011.03.003

Wu, J.-H., & Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management*, *43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Yan, L., & Tan, Y. (2014). Feeling blue? Go online: An empirical study of social support among patients. *Information Systems Research*, *25*(4), 690-709.

Zaltman, G., & Moorman, C. (1988). The importance of personal trust in the use of research. *Journal of Advertising Research,* 16-24.

Zhang, X., Liu, S., Wang, L., Zhang, Y., & Wang, J. (2019). Mobile health service adoption in China: Integration of theory of planned behavior, protection motivation theory and personal health differences. *Online Information Review*, *44*(1), 1-23. https://doi.org/10.1108/OIR-11-2016-0339

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.

Zhou, T. (2012). Examining location-based services usage from the perspectives of Unified Theory of Acceptance and use of technology and privacy risk. *Journal of Electronic Commerce Research*, *13*(2).