

FACTORS DRIVING THE ADOPTION OF ONLINE MEDICAL PLATFORMS BY INFECTIOUS DISEASE PATIENTS: PSYCHOLOGICAL DISTANCE AS THE MEDIATOR

Qianrui Du*¹, Tongjai Yampaka²

1. Chakrabongse Bhuvanarth International Institute for Interdisciplinary Studies (CBIS), Rajamangala University of Technology Tawan-ok, Thailand
2. Department of Business Administration and Information Technology, Rajamangala University of Technology Tawan-ok, Thailand

Correspondence: qianrui.du@rmutto.ac.th

ABSTRACT

INTRODUCTION

Managing common infectious diseases is becoming more challenging for public health. Patients often face high infection risks, limited medical resources, complex treatment procedures, psychological stress, and unequal access to information. This study is based on the Technology Acceptance Model and Construal Level Theory. It uses Covariance-Based Structural Equation Modeling (CB-SEM) to examine how psychological distance, perceived usefulness, and perceived ease of use influence patients' intention to use online medical platforms.

METHODS

To enhance the healthcare experience for patients with infectious diseases, this study examines psychological distance as a mediating factor in the adoption of telemedicine. We conducted a structured survey with 563 patients in Guangdong Province, China, from June 2023 to July 2024. We analyzed the relationships among perceived usefulness, perceived ease of use, psychological distance, and behavioral intention using AMOS and SPSS 22.0.

RESULTS

The results show that perceived usefulness greatly increases perceived ease of use. Psychological distance was found to mediate the effects of both perceived usefulness and perceived ease of use on patients' intention to adopt telemedicine services ($p < 0.05$). The CB-SEM analysis confirms the theoretical consistency and demonstrates the model's flexibility. These findings suggest that psychological distance is a crucial mechanism through which perceived usefulness and ease of use influence the adoption of telemedicine among patients with infectious diseases.

CONCLUSIONS

Three factors—perceived usefulness, perceived ease of use, and psychological distance—affect the adoption of telemedicine. Among these, psychological distance acts as a key mediator. When telemedicine platforms reduce psychological distance in four areas (temporal, spatial, social, and situational), they significantly increase the willingness of infectious disease patients to use remote healthcare services.

KEYWORDS

technology acceptance model; construal level theory; telemedicine; online medical platforms; CB-SEM.

INTRODUCTION

Today, digital adoption is a widespread phenomenon driving change in sectors like healthcare, education, business, and government[1, 2]. The success of online learning, remote work tools, and telemedicine largely depends on users' willingness to adopt and regularly use these new technologies[3, 4]. Adoption is influenced not only by technical factors, such as ease of use and usefulness, but also by psychological perceptions, including trust, risk, and psychological distance[5, 6]. Therefore, understanding digital adoption mechanisms requires both an information systems approach and insights from psychology and sociology.

The importance of digital healthcare is even more crucial in caring for patients with infectious diseases[7]. Because they have high incidence and transmissibility, contagious diseases continue to burden public health systems worldwide, threatening not only individual health but also social stability[8]. For example, in 2023, Guangdong Province in China reported over 18.7 million cases of notifiable infectious diseases and 26,900 deaths, illustrating the heavy burden on the healthcare system. Given the limited resources of traditional healthcare, digital healthcare is seen as a key alternative, helping to alleviate resource constraints, reduce the risk of cross-infection, and directly impact patient health and the effectiveness of public health prevention and control measures[9].

To better understand patient adoption of digital health, the Technology Acceptance Model (TAM) has been widely utilized by researchers[10]. Building on TAM, the Unified Theory of Acceptance and Use (UTAUT2) [11, 12] model considers multiple factors, such as trust, privacy concerns, digital health literacy, and hedonism, enhancing its ability to explain consumer-centric healthcare scenarios[13, 14]. However, these models primarily focus on technology and rational evaluation, failing to fully grasp the psychological decision-making processes of patients in high-risk and uncertain situations.

To address this limitation, Construal Level Theory (CLT)[15] offers a new perspective within cognitive psychology for studying digital health adoption. CLT proposes that closer psychological proximity leads to more concrete processing of information and actions[16]. Previous research has demonstrated a strong connection between psychological proximity, risk perception, and behavioral intention [17, 18]. For example, when social psychological proximity is high, individuals tend to perceive risks more acutely and are more likely to take protective or medical measures[19]. Additionally, a systematic review highlights that factors such as trust, technology quality, and privacy concerns are strongly linked to the intention to adopt digital health solutions[20]. However, no research has yet specifically explored how technological features influence patients' adoption of telemedicine through psychological proximity.

So far, existing research has not adequately integrated technological factors with psychological mechanisms. In particular, the fundamental ways in which technological features influence patients' adoption of digital health through psychological distance remain unclear. In other words, patients' decisions are often affected by both technological attributes (such as ease of use and usefulness) and psychological perceptions (such as risk and trust). However, the interaction between these two factors has not been systematically empirically validated. Therefore, this study aims to incorporate CLT into the TAM framework, using psychological distance as a mediating variable to explore its role in telemedicine adoption and to emphasize both the universality and specificity of health technology adoption within the broader context of digital adoption theory.

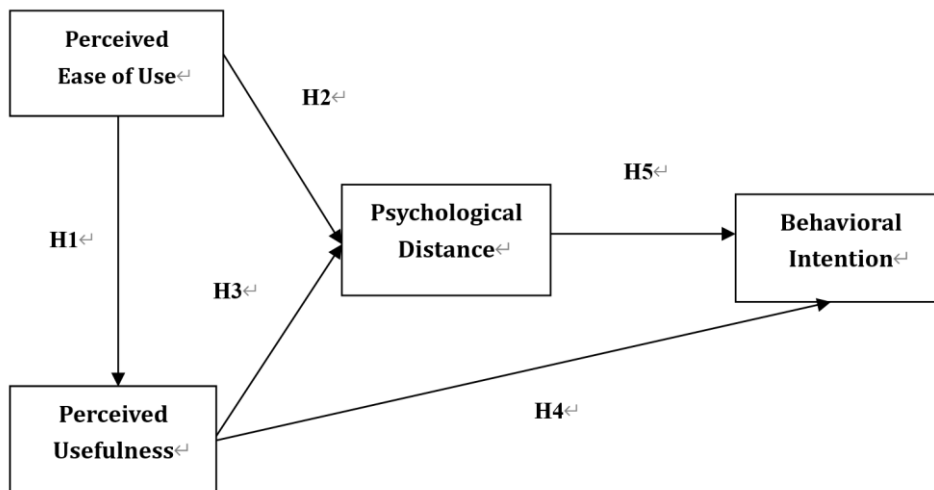
MATERIALS AND METHODS

This study surveyed patients with infectious diseases in Guangdong Province, China, and obtained 563 valid responses between June 2023 and May 2024. The sample size met the requirements for CB-SEM. Data were collected via an online questionnaire distributed through the Wenjuanxing platform [21] and accessed by QR code. Screening questions confirmed participants had both experienced an infectious disease and used an online medical platform. A 5-point Likert scale was employed to reduce bias, and anonymity was strictly maintained. On average, the survey took 10 minutes to

complete. Missing data were treated with multiple imputations in SPSS 22.0, followed by data cleaning and consistency checks.

The study employed TAM as its primary framework and incorporated CLT to extend the model. Most constructs were measured reflectively, allowing CB-SEM to assess overall model fit. The research examined how perceived ease of use (PEOU), perceived usefulness (PU), and psychological distance (PD) affect patients' intention to adopt telemedicine (BI). PD was modeled as both a direct determinant of BI and an indirect factor shaping PEOU and PU. This design enabled exploration of PD's role in technology adoption under conditions of high infection risk or psychological stress, offering a methodological basis for optimizing online medical platforms. The proposed model is presented in Figure 1.

FIGURE 1. RESEARCH MODEL.



Therefore, we make the following assumptions:

H1: PEOU has a positive and significant effect on PU.

H2: PEOU has a significant negative impact on PD.

H3: It is hypothesized that PU has a significant adverse effect on PD.

H4: A strong positive relationship exists between PU and BI among patients.

H5: The BI is significantly negatively affected by PD.

H6: The connection between PEOU and BI is mediated by PD.

H7: The connection between PU and BI is mediated by PD.

PARTICIPANTS

This study's sample includes all reported cases of statutory infectious diseases in Guangdong Province from June 2023 to May 2024, totaling 3,595,302 individuals. The cases encompass non-life-threatening contagious diseases, such as SARS, avian influenza, all types of hepatitis, dengue fever, tuberculosis, infections caused by the novel coronavirus, and influenza. A random sampling method was used, giving each person an equal chance of selection. This approach improved the sample's representativeness. The technique helped reduce bias and ensured the sample reflected the overall population. Sampling was conducted using an anonymized patient database provided by the Guangdong Provincial Health Commission. A computer-generated random number table ensured randomness of selection.

To ensure sample relevance and validity, the following inclusion criteria were applied: (a) a history of infectious disease, such as COVID-19, hepatitis, or tuberculosis; (b) use of an online medical platform for infectious disease consultation within the past year; (c) age of at least 18 years and the ability to complete the questionnaire independently; and (d) voluntary participation with signed informed consent. In strict adherence to ethical standards, informed consent was obtained before participants completed the questionnaire, and all data were anonymized and approved by the relevant ethics committee.

According to Yamane's sample size calculation formula[22], the required minimum sample size was at least 399. The number of questionnaires distributed was increased to account for invalid or unanswered responses. Based on Krejcie and Morgan's recommendation, and assuming a 60% response rate, the adjusted number of questionnaires to be distributed was approximately 665 (i.e., $399 / 0.6$).

A total of 665 questionnaires were distributed to patients with infectious diseases, yielding 563 valid responses for analysis. Data were collected using structured survey tools, and all procedures were conducted in accordance with ethical standards and approved by the relevant ethics committee.

The final sample description shows that 48.31% of respondents were male and 51.69% were female. Most participants were between 18 and 50 years old (84%, $M = 30.33$, $SD = 12.58$). Regarding education, 31.61% had a junior high school education or less, 25.58% were junior college students, and 42.81% were college students. Additional sociodemographic and academic details are provided in **Table 1**.

TABLE 1. SOCIODEMOGRAPHIC AND ACADEMIC CHARACTERISTICS OF THE SAMPLE.

Variables	N=563	%Sample
Gender		
Male	272	48.31%
Female	291	51.69%
Age		
Range	18-50	84%
Mean	30.33	
Education		
High school or less	178	31.61%
College	144	25.58%
University	220	39.08%
Master and above	21	3.73%
Monthly Income		
Less than 5,000 CNY	245	43.5%
5,000-10,000 CNY	223	39.6%
10,000-15,000 CNY	72	12.8%
More than 15,000 CNY	23	4.1%

ETHICS

This study was conducted in strict compliance with international ethical standards. Ethical approval was obtained from an institutional ethics committee in Guangdong Province, China. The approval reference number was not available, and all procedures adhered to the Declaration of Helsinki[24] and the Ethical Review Methods for Biomedical Research Involving Humans (National Health Commission of China, 2016)[25]. Given that participants were patients with infectious diseases (e.g., tuberculosis, hepatitis, HIV/AIDS), special safeguards were applied to protect this vulnerable group.

All participants provided informed consent after being fully informed of the study objectives, data use, privacy protection, and their right to withdraw at any time. Data were collected anonymously, securely stored with encryption and restricted access, and contained no personal identifiable information.

The study followed the GATHER reporting checklist, which is more suitable for cross-sectional observational research than CONSORT or SPIRIT. This ensured transparency in study design, data handling, and participant protection. A detailed mapping to the checklist is provided in Appendix A.

Due to ethical restrictions, raw datasets cannot be made publicly available. Still, de-identified summary data may be obtained from the corresponding author upon reasonable request and ethics committee approval.

MEASUREMENT INSTRUMENTS

The questionnaire had two sections. The first gathered demographic information. The second assessed core constructs—PD, PU, PEOU, and BI—using 15 items adapted from validated scales, rated on a 5-point Likert scale. Table 2 shows the measurement items.

TABLE 2. MEASUREMENT ITEMS OF CONSTRUCTS.

Construct	Variables	Measurement Items	Source
Perceived Ease of Use	PEOU1	I find the online consultation platform easy to use.	[26, 27]
	PEOU2	It is straightforward to locate the necessary information on the online consultation platform.	
	PEOU3	I can interact with doctors quickly through online consultation platforms.	
	PEOU4	It has become easier to seek medical advice for my health problems through the online consultation platform.	
Perceived Usefulness	PU1	The online consultation platform is highly effective in addressing my medical needs.	[26, 28]
	PU2	The online consultation platform enables me to receive medical consultation more quickly than at traditional hospitals.	
	PU3	The online consultation platform enables me to access medical services within a limited timeframe.	
	PU4	Using an online consultation platform helps me better understand how to manage my health.	
Psychological Distance	PD1	I would use the online consultation platform whenever I have concerns about my symptoms.	[16, 18, 29]
	PD2	If I lived in a remote area or found it difficult to visit a hospital, I would choose to use the online consultation platform.	
	PD3	I trust the doctors on the online consultation platform, even if I don't know them personally.	
	PD4	I believe online consultations can accurately diagnose and effectively treat my health issues.	
Behavioral Intention	BI1	I believe an online consultation platform is a valuable tool that is worth utilizing in the long term.	[26, 30]
	BI2	I am likely to continue using the online consultation platform in the future.	
	BI3	I would recommend the online consultation platform to others.	

STATISTICAL ANALYSES

Statistical analysis was performed in two phases. First, the reliability and validity of the measurement tool were evaluated. Reliability was measured using Cronbach's α , and validity was assessed through content and construct validity, as well as Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). The model was deemed acceptable with factor loadings above 0.4, a KMO value greater than 0.6, and a significant Bartlett's test ($p < 0.05$). Correlations among variables were examined using Pearson's coefficient, and the mediating effect of psychological distance was tested with 5,000 bootstrap samples.

In the second stage, the SEM was constructed and estimated using the Maximum Likelihood method, along with 5,000 bootstrapped confidence intervals. SEM was used to examine both direct and indirect effects of psychological distance on user adoption behavior. Model fit was evaluated using multiple indices: non-significant chi-square ($p > 0.05$), RMSEA < 0.08 , SRMR < 0.06 , and CFI and TLI > 0.95 . All analyses were performed in SPSS 22.0 and AMOS.

RESULTS

THE MEASUREMENT MODEL ANALYSES

Reliability Analyses

The Cronbach's α analysis (Table 3) confirmed the survey results' reliability. All variables showed strong internal consistency, with PEOU (0.845), PU (0.853), PD (0.863), and BI (0.814), each exceeding the widely accepted threshold of 0.70. These findings demonstrate high reliability and support the validity of the questionnaire. Conversely, values below 0.70 generally indicate potential issues with item consistency on Likert scales.

TABLE 3. CRONBACH'S RELIABILITY ANALYSIS.

Variables	Number of items	Cronbach's α coefficient
PEOU	4	0.845
PU	4	0.853
PD	3	0.863
BI	3	0.814

Validity Analyses

The measurement model was assessed for reliability using Cronbach's α and Composite Reliability (CR), and for construct validity through CFA. Internal reliability was confirmed by the Cronbach's α coefficients listed in **Table 4**. The internal consistency of the latent constructs was further verified with CR after confirming that all standardized factor loadings exceeded 0.70. The CR values—each above 0.70—provided strong evidence of internal consistency, confirming the measurement model's solid reliability.

The KMO value was 0.887 ($p < 0.05$), significantly higher than the 0.60 threshold, indicating that the model is suitable for factor analysis. Convergent validity was assessed using the AVE, which measures the proportion of variance in a construct that is captured relative to measurement error. As shown in **Table 4**, all AVE values exceeded 0.50, confirming strong convergent validity. Additionally, VIF values for all constructs were below 2.2, indicating there is no significant multicollinearity.

TABLE 4. RELIABILITY AND VALIDITY.

Constructs	Loading Factor	CR	AVE	VIF
PEOU	0.618-0.705	0.799	0.665	1.940-1.992
PU	0.692-0.716	0.785	0.694	2.008-2.087
PD	0.686-0.724	0.803	0.658	2.042-2.188
BI	0.653-0.697	0.718	0.503	NA

CORRELATION ANALYSES

An analysis of the Pearson correlation matrix shown in Table 5 examined the relationships among PU, PEOU, BI, and PD. The results revealed statistically significant negative correlations between PD and PU ($r = -0.401$), PEOU ($r = -0.403$), and BI ($r = -0.413$). These coefficients indicate moderate inverse relationships, suggesting that as PD increases, the other variables tend to decrease in value.

Positive correlations were also observed: PU was positively related to PEOU ($r = 0.422$) and BI ($r = 0.417$), indicating that higher PU is linked to increased PEOU and a stronger BI. Additionally, a moderate positive correlation ($r = 0.363$) was found between PEOU and BI. These findings highlight the mutually reinforcing relationships among the three key constructs.

TABLE 5. OBSERVED VARIABLES CORRELATION COEFFICIENT. (N=563)

	PEOU	PU	PD	BI
PEOU	1			
PU	.422**	1		
PD	-.403**	-.401**	1	
BI	.363**	.417**	-.413**	1
MEAN	3.3	3.27	2.69	3.35
SD	1.215	1.227	1.222	1.219

KMO Measure of Sampling Adequacy = 0.943; Bartlett's Test of Sphericity Approx. Chi-square = 4266.553, df=105, $p = .000$

STRUCTURAL MODEL ANALYSES

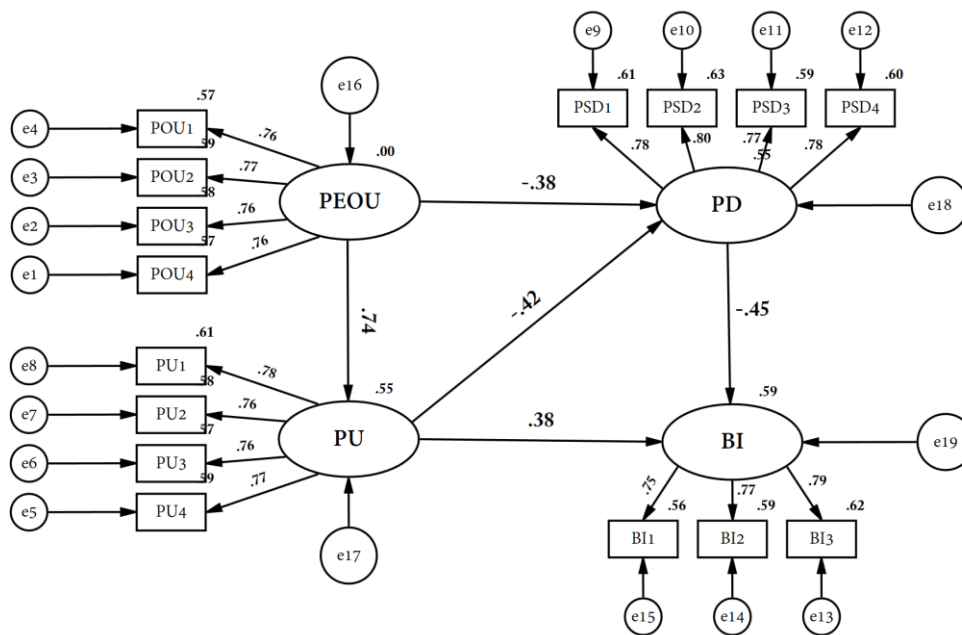
After confirming the measurement model's reliability and validity, the next step was to use the structural model to test the research hypotheses. The overall fit of the theoretical model was assessed using several indices, as shown in Table 6. The model demonstrated an excellent fit, with all fit indices meeting the required statistical standards.

TABLE 6. MODEL FIT

INDEX	NFI	RFI	IFI	CFI	GFI	AGFI	CMIN/DF	RMSEA
Value	0.980	0.975	0.999	0.999	0.979	0.971	1.047	0.009

The absolute fit indices, including CMIN/DF = 1.047 and RMSEA = 0.009 (90% CI [0.000, 0.025], PCLOSE = 1.000), indicate an excellent model fit with minimal residual variance. The incremental fit indices — NFI = 0.980, IFI = 0.999, CFI = 0.999 — show significant improvements over the null model. Additionally, the GFI (0.979) and AGFI (0.971) further support the model's strong fit. In summary, the model demonstrates an outstanding overall fit, effectively explains the observed data, and provides full support for the proposed theoretical framework.

FIGURE 2. PATH COEFFICIENTS FOR THE WHOLE MODEL.



Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Chi-Square=89.0, df=85, P-value=0.362, RMR=0.038

Figure 2 shows the results of the structural model. The analysis revealed that the following paths were significant: PU ← PEOU ($t=13.743$, $\beta =0.748$), PD ← PEOU ($t=-5.520$, $\beta =0.391$), PD ← PU ($t=-6.153$, $\beta =-0.402$), BI ← PD ($t=-7.093$, $\beta =-0.469$), and BI ← PU ($t=6.036$, $\beta =0.402$). These findings support hypotheses H1 through H5. A summary of the hypothesis testing results is shown in Table 7.

TABLE 7. HYPOTHESIZED RELATIONSHIPS. *, P=0.001, 95% CONFIDENCE LEVEL.**

Hypotheses	Paths	t	β	p	Comments
H1	PU ← PEOU	13.743	0.748	***	Supported
H2	PD ← PEOU	-5.520	0.391	***	Supported
H3	PD ← PU	-6.153	-0.402	***	Supported
H4	BI ← PU	6.036	0.402	***	Supported
H5	BI ← PD	-7.093	-0.469	***	Supported

MODERATED MEDIATION ANALYSES

A mediating variable acts as an intermediary process through which the effect of an independent (latent) variable is transmitted to a dependent variable. In this study, the Bootstrap method was used with SPSS to test for mediation effects. The empirical sampling distribution was employed to estimate the parameters. An iterative resampling process was conducted (N = 563, with 5,000 repetitions) to determine the 95% confidence interval.

The results presented in Table 8 show that the confidence intervals for both hypothesized mediating pathways do not include zero, and all associated p-values are below the 0.05 significance level. This verifies that the mediation effects are both valid and statistically significant.

TABLE 8. BOOTSTRAPPED MEDIATION ANALYSIS

Mediation Path	Corresponding	Estimate(β)	Lower	Upper	P
PEOU-PD-BI	H6	0.1290	0.0909	0.1716	p<0.0001
PU-PD-BI	H7	0.1171	0.0784	0.1601	P<0.0001

Specifically, psychological distance acts as a mediator in the relationships between perceived usefulness, perceived ease of use, and the intention to adopt. Therefore, Hypotheses 6 and 7 are supported. These results enhance the understanding of how these key factors interact and influence each other, confirming the validity of the TAM in this research context. Furthermore, all hypotheses were tested and confirmed within the framework of the CLT. According to the structural equation model analysis, the model fits the data well and has strong explanatory power.

DISCUSSION

This study combines TAM with CLT to examine how PD influences telemedicine adoption. The results indicate that PD is not merely a fixed background factor; instead, it functions as an active psychological regulator that affects the pathway from PU and PEOU to BI through trust and anxiety.

PD plays a dual role in changing how people see technology into their behavioral intentions. Cutting down on time and space (for example, instant consultations, online prescriptions, home care) reduces mental effort and increases PEOU. At the same time, shrinking social and situational gaps (such as clear physician credentials and patient review systems) help build trust and ease anxiety, which boosts the effect of PU on BI. The different effects across the four PD dimensions highlight the importance of considering PD as a multidimensional concept rather than a single idea.

THEORETICAL CONTRIBUTIONS

This research contributes to existing literature in three keyways:

1. Validation: In high-risk healthcare settings, TAM's main mechanisms stay strong, with PU and PEOU serving as key factors in telemedicine adoption.
2. Extension: By incorporating CLT, the study shows the mediating role of PD and its different aspects, addressing TAM's narrow focus on psychological mechanisms.
3. Reconceptualization: PD is redefined from a static outcome to a dynamic driver, resulting in a three-stage framework—cognition, psychological mechanisms, and behavioral intention—that offers a more detailed explanation of digital health adoption.

LIMITATIONS

Several limitations of this study should be acknowledged. First, the sample was limited to Guangdong Province, which may restrict how broadly the findings apply. Second, the cross-sectional design and reliance on self-reported data may introduce recall and social desirability biases, particularly in the sensitive context of infectious diseases, which can prevent firm causal conclusions. Third, potential confounding factors such as digital skills, prior telemedicine experience, socioeconomic status, and platform reputation were not considered. Future research could address these limitations by employing longitudinal or multi-wave designs to examine the stability of psychological distance mechanisms over time, incorporating behavioral or platform usage data to supplement self-reports, and utilizing experimental manipulations of psychological distance to provide stronger causal evidence. Despite these limitations, the study offers valuable theoretical and practical insights, and these suggested directions give a clear roadmap for future research to enhance causal claims and expand empirical validation.

CONCLUSIONS

By combining TAM and CLT, this study highlights the crucial role of PD in the adoption of telemedicine. PU and PEOU remain key factors, while PD affects their influence on BI through trust and anxiety, showing apparent differences across dimensions. These findings enhance the understanding of health technology adoption and offer a flexible psychological framework for a broader range of digital adoption scenarios.

From a practical perspective, telemedicine platforms should enhance usability, transparency, and trust while strategically lowering psychological barriers to improve user experience. Policymakers should support insurance coverage, set clear legal and technical standards, and invest in digital infrastructure, all while addressing users' psychological needs and cultural differences to encourage adoption and ensure the long-term success of telemedicine services.

AUTHORSHIP STATEMENT

All authors of this paper have agreed to submit it for review and meet the authorship criteria, including substantial contributions to the conception, design, execution, methodological input, data analysis, and interpretation of the study. All authors have reviewed and approved the final version of the manuscript and confirmed the appropriateness of the authorship order.

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CONFLICT OF INTEREST STATEMENT

The authors declare no financial or personal conflicts of interest that could influence this study.

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APPENDIX A

GATHER CHECKLIST MAPPING FOR THIS STUDY

GATHER Item	Description	Where Reported
1. Objectives	Clearly state the research objectives and questions	INTRODUCTION, MATERIALS AND METHODS
2. Study Design	Specify the type of study (cross-sectional online survey)	MATERIALS AND METHODS PARTICIPANTS
3. Data Sources	Describe data sources (online questionnaire, patient recruitment channels)	PARTICIPANTS
4. Participants	Eligibility criteria, inclusion/exclusion rules, and sample size	PARTICIPANTS
5. Data Collection Methods	Explain how the data were collected (online platform, timeframe)	PARTICIPANTS
6. Data Processing	Handling of missing data, cleaning procedures, and anonymization	MATERIALS AND METHODS
7. Ethical Safeguards	Ethical approval, informed consent, and protections for vulnerable groups	PARTICIPANTS ETHICS
8. Risk of Bias	Measures taken to minimize bias (sampling strategy, survey design)	PARTICIPANTS MEASUREMENT INSTRUMENTS
9. Limitations	Limitations of the study and implications for interpretation	DISCUSSION
10. Data Availability	Statement on data sharing and access restrictions	ETHICS