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A study on factors influencing user satisfaction and interaction with mobile healthcare technologies

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ABSTRACT

This paper examines the predictors of user satisfaction (US) and user interaction (UI) with mobile healthcare technologies, perceived ease of use (PEU), perceived usefulness (PU), information quality (IQ), privacy and security, and personalization. It also tests the mediating factor of user trust (UT) and the moderating factor of technology readiness (TR). Using a quantitative design, 280 mobile healthcare users in China were recruited through a structured questionnaire, with measurement scales based on validated studies. Data analysis was performed in SmartPLS to estimate measurement and structural models, as well as direct, mediating, and moderating relationships. The findings indicate that the five system characteristics have a strong and positive effect on US and UI. UT facilitates the impacts of these characteristics on both outcomes, while TR reinforces the correlations between UT and US/UI. The impacts of UT are stronger among more prepared users. By integrating the Technology Acceptance Model (TAM), the Information Systems Success Model (ISSM), and trust-based approaches, this study provides a comprehensive context for understanding mobile healthcare technology adoption. The results offer valuable theoretical and practical implications for system developers, healthcare professionals, and policymakers, emphasizing the importance of usability, information quality, security, personalization, trust, and technology readiness. This study is among the few that examine trust and readiness as factorial mechanisms influencing mobile healthcare engagement and satisfaction.

Contribution/Originality: This study contributes to combining TAM and ISSM differences with trust theory by modeling user trust as an intermediary and technology readiness as a conditional angle within a single construct to clarify post-adoption satisfaction and interaction in mobile healthcare, a contingency not easily detailed in the empirical analysis.

1. INTRODUCTION

The versatile development of mobile technologies has revolutionized the healthcare sector considerably, providing novel possibilities to improve patient care, access, and involvement in healthcare management (Sitaraman, 2025). Mobile health technologies, such as mobile applications, wearables, and telemedicine platforms, are becoming commonplace for delivering tailored, real-time, and cost-efficient technological solutions to healthcare (Kim, 2024). Such technologies can empower patients by allowing them to have more control over their health-related choices and can simplify the way health professionals monitor, diagnose, and treat conditions (Dhote, Baskar, Shakeel, & Dhote, 2023). The adoption of digital tools in healthcare is also aligned with global healthcare initiatives to enhance health outcomes and reduce healthcare expenses, especially in areas with limited resources (Kitsios, Stefanakakis, Kamariotou, & Dermentzoglou, 2023). Mobile healthcare technologies are becoming a necessity with the increase in smartphone penetration and digital literacy, and they can be used to promote preventive care and management of chronic illnesses (Tenggono, Soedjipto, & Sudhartio, 2024).

A large amount of empirical data has been investigated on the factors that determine US contact with mobile healthcare technologies (Ghadi et al., 2024). As an example, research based on the Technology Acceptance Model has consistently demonstrated that the PEU and PU are the main predictors of technology acceptance and satisfaction (Cheema, Ahmed, Iqbal, & Naz, 2025). The ISSM studies have also emphasized IQ in creating positive user experiences, especially when making health-related decisions based on available and correct information (Zhan, Abdi, Seymour, & Such, 2024). Trust has also been revealed to play a core role in the adoption of technology, with research showing that UT lowers risk perception and reinforces further interaction (Cao, Feng, Lim, Kodama, & Zhang, 2024). Furthermore, the issues related to privacy and security are generally recognized as the determining factors in healthcare technology adoption, as users are especially sensitive to the security of sensitive health information (Rahardja, Sunarya, Aini, Millah, & Maulana, 2024).

Although the literature is increasing, there are still some critical research gaps in the knowledge of the US and its interaction with mobile healthcare technologies (Çavmak, Söyler, & Çavmak, 2024). Much of the existing work has generally concentrated on technology acceptance of general information systems without paying particular attention to the requirements of the healthcare setting, where trust, privacy, and security contribute disproportionately to such research (Lee, Ramasamy, & Subbarao, 2025). Although UT has been studied in some cases, no studies have investigated the relevance of trust in the relationships between the system features, including ease of use, usefulness, IQ, and personalization, and the UI outcomes in a systematic manner (Bahari, Mutambik, Almuqrin, & Alharbi, 2024). Likewise, empirical studies often focus on adoption intention rather than post-adoption experiences and do not provide much information on how satisfaction and enduring interaction are realized (Kitsios et al., 2023). This disparity demonstrates the necessity for more comprehensive frameworks that incorporate trust as a mediating variable and consider context-specific effects in a mobile healthcare setting.

The other gap is that there is not much focus on individual user differences, including TR, which can serve as a boundary condition in determining technology outcomes (Salvador-Carulla, Woods, de Miquel, & Lukersmith, 2024). Although trust is essential in the adoption of healthcare technologies, its impact on the levels of satisfaction and interaction might also differ with regard to users' willingness to adopt new technologies (Shonubi, 2024). Nevertheless, the literature that specifically studies the moderating impact of TR in a medical environment is limited, and the majority of the literature analyzes its direct impact on adoption instead of the interactive outcomes of TR (Leung & Cheung, 2025). With the help of removing these limitations, the study aims to offer a deeper insight into the interaction of the impact of technical, informational, psychological, and individual difference factors on satisfaction and interaction with mobile healthcare technologies. To address these gaps, the current research intends to explore the determinants of US and interaction with mobile healthcare technologies, and analyze the mediating effect of UT and the moderating effect of TR. The aims of the study are:

- To test the direct impact of PEU, PU, IQ, privacy and security, and personalization on the US and UI.
- To examine the mediating effect of UT in the correlation between the system characteristics (PEU, PU, IQ, privacy and security, personalization) and the US and interaction.
- To test the moderating effect of technological preparedness in enhancing the relationship between UT and US and between UT and UI.

The study is important as it contributes to the theoretical and practical development of the sphere of mobile healthcare technologies. Ideally, the research's contributions include the synthesis of constructs from TAM, the Information System Success Model, and trust theory, along with the addition of the moderating influence of TR, making the research applicable across healthcare environments to expand current frameworks (Gefen, Karahanna, & Straub, 2003; Lin, 2007). Practically, the findings will inform developers, medical practitioners, and policymakers with viable recommendations on designing, launching, and marketing mobile healthcare technologies capable of ensuring adoption as well as sustaining a US level of interaction (Kapoor, 2018; Smith, 2018). The focus on the significance of trust, personalization, and TR can assist the study in guiding the creation of strategies that address users' concerns and interests, ultimately contributing to improved healthcare outcomes due to higher patient engagement. By doing so, the study helps bridge the gap between technological innovation and patient-centered healthcare provision, positioning mobile healthcare technologies as a vital component of the future of digital health.

2. LITERATURE REVIEW

The increased use of mobile healthcare technologies has brought about a significant change in the provision of healthcare services through real-time health monitoring, improved communication between patients and service providers, and personalized interventions. Previous research indicates that ease of use, system quality, service quality, and the reliability of the information presented to users have greatly influenced user satisfaction with such technologies (Davis, 1989). An example of this is that the PEU and PU, which are key elements of TAM, have often been mentioned as significant predictors of long-lasting usage of mobile health applications (Venkatesh, 2000). Moreover, trust and data security are important, since people usually worry about the confidentiality of sensitive medical data, which subsequently affects their degree of satisfaction and readiness to cooperate with such platforms (Sitaraman, 2025). Studies also highlight that in the case of mobile healthcare applications providing users with reliable, timely, and personalized information, the likelihood of user satisfaction and active engagement with the technology increases, thereby enhancing health management behaviors (Dhote et al., 2023; Rahardja et al., 2024; Zhan et al., 2024). The other aspect that is critical in determining how users interact with mobile healthcare technologies is the effect of design elements and aspects of user experience. Research indicates that well-designed interfaces, interactive features, and responsive feedback systems help to achieve good user experiences, as well as promote sustained interactions (Cao et al., 2024). There are also contextual elements, e.g., age, digital literacy, and cultural attitudes towards technology, which can make the user either happy or discouraged by the adoption of the technology (Or et al., 2011). To illustrate, older users may require a less difficult design and more instructions than younger users, who tend to be more technologically minded (Ahn & Park, 2023). In addition, the continuous update and combination of the capabilities of artificial intelligence, i.e., predictive analytics and chatbots, have been shown to enhance the perceived usefulness (PU), contributing to satisfaction levels and engagement (Kim, 2024).

2.1. Hypothesis Development

PEU and PU have always been identified as important determinants of user satisfaction in mobile healthcare technologies. Empirical research indicates that users tend to have positive attitudes and remain engaged when they believe that a system is easy to navigate and interact with; this increases overall satisfaction (Tenggono et al., 2024). Similarly, PU, which refers to the extent to which users believe that a technology will help them manage their health or make better health decisions, has been found to have a positive relationship with satisfaction across various mHealth applications (Cheema et al., 2025). According to the evidence provided by studies on patient-centered mobile applications, ease of use and usefulness are equally important aspects in increasing satisfaction rates, as users tend to focus on the intuitive interface and precise, actionable health information when working with these technologies (Ali, Singh, & Gowindasamy, 2024). Considering this empirical evidence, the study indicates that the maximization of these factors can have a direct effect on user satisfaction, and it can be used to make a strong argument in attempting to hypothesize the positive effects (Sitaraman, 2025).

The other aspect of US shaping both the functional and psychological needs is IQ, privacy, security, and personalization (Ranjbar et al., 2024). Accuracy, relevance, and timeliness have been associated with high-quality information, which has increased trust and confidence in mobile healthcare platforms, thus increasing satisfaction (Dhote et al., 2023). Other empirically linked elements of satisfaction are the privacy and security measures, such as encryption, secure authentication, and an open policy regarding the use of data, which have been demonstrated to be critical items in satisfaction (Nazari-Shirkouhi, Badizadeh, Dashtpeyma, & Ghodsi, 2023). Additionally, personalization, including customized recommendations, adaptive reminders, user-specific feedback, and so on, proved to promote engagement and perceived value, which has a positive impact on the level of satisfaction (Rahardja et al., 2024). Taken together, these results substantiate the formulation of hypotheses according to which IQ, privacy and security, and personalization have a strong positive impact on the US, which implies the multidimensionality of the factors that promote successful interaction with mobile healthcare technologies.

H_{1a}: PEU has a positive effect on the US.

H_{1b}: PU has a positive effect on the US.

H_{1c}: IQ has a positive effect on the US.

H_{1d}: Privacy & Security has a positive effect on the US.

H_{1e}: Personalization has a positive effect on the US.

PEU has been repeatedly associated with a greater degree of UI under various circumstances of technology adoption (Lee et al., 2025). Interaction here is an indicator of how much the user is participating in the system features actively and for continued use. Previous studies suggest that the more a mobile healthcare application is easy to navigate and use, the more often users tend to engage with it and utilize its features (Binzer, Kendziorra, Witte, & Winkler, 2023; Fang, Zhou, Ying, & Li, 2023; Kim, 2024; Mazaheri Habibi, Moghbeli, Langarizadeh, & Fatemi Aghda, 2024). Research in digital health platforms shows that users are less likely to engage with a complex design or when they find it difficult to access the core functions, but more likely to engage when the system functions are simple, and they can engage in repeated interaction and deeper engagement (Çavmak et al., 2024). Likewise, PU has also been established as one of the key determinants of interaction with technologies, with users more inclined to develop interactions with those applications they believe will add value to their health management processes (Shonubi, 2024). IQ also has a significant role in promoting UI using mobile healthcare technologies. Information of high quality, in terms of relevance, timeliness, and accuracy, enhances user engagement, as users will want to revisit the system to obtain dependable information (Ignacio & Paras, 2024). According to evidence from e-health platforms, users are more engaged with technologies that deliver credible and comprehensive information based on their healthcare requirements (Dermody et al., 2025). The issue of data security is especially relevant in the healthcare industry, where users can disclose very sensitive data, and studies indicate that a high level of privacy enhances trust and encourages people to use digital health services more often (Nie, Oldenburg, Cao, & Ren, 2023). More so, personalization has become a key motivation behind UI, where customization (individualized reminders, personalized health advice, flexible interfaces, etc.) promotes relevance and can generate meaningful user experiences (Liu, Zhang, Liu, & Lai, 2023).

H_{2a}: PEU has a positive effect on UI.

H_{2b}: PU has a positive effect on UI.

H_{2c}: IQ has a positive effect on UI.

H_{2d}: Privacy & Security has a positive effect on UI.

H_{2e}: Personalization has a positive effect on UI.

UT has gained popularity as an imperative moderator in establishing the success of technology adoption, especially in sensitive areas like mobile healthcare. Trust is the attitude that a system is dependable, safe, and capable of producing the expected results, which is one of the key elements in defining how people are satisfied with digital platforms (Mohammed & Rozsa, 2024). Empirical research shows that PEU improves trust since users are more assured when navigating an intuitive and user-friendly system, which in turn enhances satisfaction (Zhan et al., 2024). Equally, PU has been determined to drive trust, whereby users tend to depend more on the application that proves to enhance their health management performance, resulting in increased satisfaction (Cao et al., 2024). Trust is also enhanced by IQ in that the relevant, right, and timely content convinces users that the system is credible; hence, mediating their overall satisfaction (Butt et al., 2023). Moreover, privacy and security features are also key trust elements, as users feel more content with a system that prevents any misuse or breach of their sensitive health data (Liu, Sorwar, Rahman, & Hoque, 2023). Personalization is also used to promote trust by demonstrating that the technology responds to users' needs, thereby increasing the perceived reliability and relevance of the technology, which leads to an increase in user satisfaction (Joshua, Abbas, Lee, & Kim, 2023). Overall, these empirical results support the idea that user trust acts as an important mediating factor, connecting core system characteristics and customized features to satisfaction outcomes. It is essential to design mobile healthcare technology to instill confidence and reliability to maximize user satisfaction.

H_{3a}: UT mediates the relationship between PEU and US.

H_{3b}: UT mediates the relationship between PU and US.

H_{3c}: UT mediates the relationship between IQ and US.

H_{3d}: UT mediates the relationship between Privacy & Security and the US.

H_{3e}: UT mediates the relationship between Personalization and US.

UT has been highly accepted as a mediating variable in the adoption and continued use of mobile healthcare technologies as a key factor through which system attributes influence UI. Trust means the user is confident in the reliability, integrity, and competency of the technology to deliver said services without exposing sensitive personal information (Rahardja et al., 2024). Empirical evidence indicates that PEU leads to trust as it alleviates perceived complexity and uncertainty and enables users to feel confident when using digital health platforms (Binzer et al., 2023). Likewise, PU builds trust since users can see real value in the use of the system, which increases the desire to actively participate in the technology (Bahari et al., 2024). The role of IQ is also important because, whenever the content is accurate, timely, and relevant, uncertainty is reduced, and users gain confidence in the system's credibility, which increases interaction (Kitsios et al., 2023). The privacy and security considerations are especially topical to foster trust in healthcare settings, where users tend to respond to platforms that guarantee the safety of sensitive medical information with efficient security controls and open privacy policies (Yum & Yoo, 2023). Moreover, personalization can build trust because it indicates that the system knows and addresses the specific health requirements of a person, which leads to the desire to engage and use it regularly (Helm, Eggert, & Garnefeld, 2010). Overall, these works suggest that UT is a key mediator, converting the perception of ease of use, usefulness, IQ, privacy, and security, and personalization into increased degrees of active engagement, making it appropriate to formulate hypotheses that the relationship between these antecedents and UI with mobile healthcare technologies may be mediated by UT (Ahn & Park, 2023).

H_{4a}: UT mediates the relationship between PEU and UI.

H_{4b}: UT mediates the relationship between PU and UI.

H_{4c}: UT mediates the relationship between IQ and UI.

H_{4d}: UT mediates the relationship between Privacy & Security and UI.

H_{4e}: UT mediates the relationship between Personalization and UI.

The concept of TR, which consists of the disposition of an individual to adopt and utilize new technologies, has become a pivotal factor in the effectiveness of digital platforms in fostering satisfaction and interaction (Çavmak et al., 2024). The high-TR population feels more confident about system experimentation, the removal of initial obstacles, and the gaining of the benefits of technology, which may increase the significance of trust in results (Aini, Manongga, Rahardja, Sembiring, & Li, 2025). Empirical research showed that technologically prepared users have higher chances of transferring their trust in a system into positive experiences of increased satisfaction and more frequent interaction than less prepared users (Musa & Deji, 2024). As an example, studies in the domain of mobile healthcare show that higher TR users not only perceive systems as more convenient and useful but also use trust to become more active users of the apps and receive the system features with a positive attitude (Wu & Lim, 2024). Such a moderating influence is especially evident in situations where systems require constant interaction or the use of complex functionalities, because technology-ready users are better able to translate their trust into valuable satisfaction and interaction behavior (Chang, Yu, Chao, & Lin, 2024). In this way, the hypothesis is that TR enhances the correlation between UT and both US and UI, which implies that the impact of trust on them depends on the degree of a person's technological competence and readiness to implement new digital solutions.

H_{5a}: TR positively moderates the relationship between UT and US, such that the relationship is stronger when TR is high.

H_{5b}: TR positively moderates the relationship between UT and UI, such that the relationship is stronger when TR is high.

2.2. Theoretical Framework Supporting the Research

The TAM and its extensions provide the foundation of the theoretical groundwork to explain the relationships in this research model, which is supplemented by the ISSM and trust-based viewpoints in technology adoption. According to TAM, PEU and PU are vital factors that determine user attitudes and behaviors regarding technology, which are directly proportional to the US and interaction hypotheses (Davis, 1989; Venkatesh, 2000). Inclusion of IQ is based on the values of the DeLone and McLean (2003) ISSM, which stresses the role of IQ as a central element that determines the use of the system and US (DeLone & McLean, 2003). Moreover, as pointed out by the trust theory, UT is a key mechanism in situations that involve sensitive data, such as mobile health, where perceived threats and privacy concerns can serve as barriers to adoption (Gefen et al., 2003). The mediating role of trust is supported by evidence suggesting that even when systems are perceived as easy to use, useful, secure, or personalized, users require trust as a psychological assurance before translating these perceptions into satisfaction or interaction. Finally, the moderation of TR draws from Parasuraman's (2000) TR Index, which explains how individual differences in optimism, innovativeness, discomfort, and insecurity toward technology shape the extent to which trust influences outcomes. Users with higher TR are more inclined to transform trust into satisfaction and interactive behaviors because they perceive fewer barriers and greater opportunities in adopting digital healthcare. Collectively, the integration of TAM, ISSM, trust theory, and TR perspectives provides a comprehensive theoretical explanation for the proposed research framework, which is illustrated in Figure 1: Conceptual Framework.

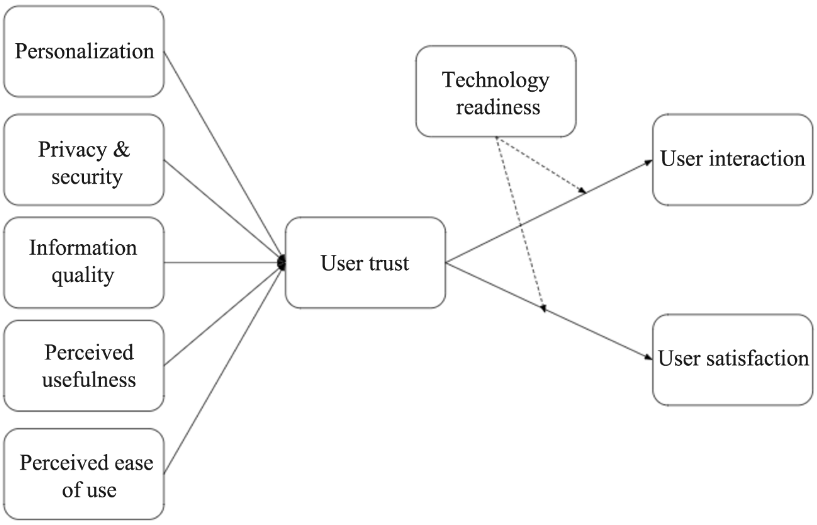

Figure 1. Conceptual Framework.

3. Methodology

3.1. Research Design

In this study, the quantitative research design was used to investigate the factors that affect user interaction with mobile healthcare technologies. The cross-sectional survey method was chosen, as it allows for the collection of data from a large number of respondents simultaneously and is commonly employed in studies of technology adoption and healthcare-related research (Hair, Sarstedt, Ringle, & Mena, 2012). Partial Least Squares Structural Equation

Modeling (PLS-SEM) with the SmartPLS software was utilized to test the structural model. This approach is suitable for complex models involving moderating and mediating variables and is appropriate for exploratory research in new settings such as mobile healthcare technologies.

3.2. Population, Sample Size, and Sampling Technique

The sample used in this study included users of mobile healthcare technologies in China, such as mobile health applications and wearable health monitoring devices. The valid sample size was 280 responses, which is considered sufficient in PLS-SEM, as a minimum of ten times the maximum number of structural paths to a construct is generally required (Hair et al., 2012). The selection of respondents involved a non-probability purposive sampling method, where individuals who had previously utilized mobile healthcare technologies were chosen to ensure that the sampled participants were educated and capable of providing relevant information. This sampling method is appropriate when the research aims to gather data from a specific group with experience in the phenomenon under investigation.

3.3. Data Collection

The questionnaire used for data collection consisted of a structured instrument administered both online and offline to obtain a diverse respondent pool. To enhance the questionnaire's validity, a back-translation technique was employed, ensuring the translation preserved the original meaning and was culturally appropriate. The translation was conducted into Chinese to facilitate better understanding among respondents and to maintain cultural relevance (Brislin, 1986). Respondents were asked to rate items on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). A total of 320 responses were collected; after screening for completeness and consistency, 280 responses were deemed valid and included in the analysis.

3.4. Measures

Measurement scales of all constructs were based on previous studies to ensure content validity. PEU and PU were evaluated with the help of the items modified according to Davis (1989) and Venkatesh (2000). The scales of DeLone and McLean (2003) ISSM were used to measure IQ. Privacy and security items were borrowed based on some previous research on online trust and adoption of e-health (Kitsios et al., 2023). The scale used to measure personalization was based on research articles on adaptive healthcare technologies. Measures of US and UI were taken based on modified versions of the Bhattacherjee (2001) and digital engagement literature scales, respectively. UT was assessed with the scales that were adjusted on the basis of trust-related literature in e-commerce and e-health (Gefen et al., 2003). Items of the TR Index of Parasuraman (2000) were used as measures of TR. All measurement items were narrowed to fit the healthcare technology scenario and assessed to determine reliability and validity before testing theories.

3.5. Data Analysis

This study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS to test the hypothesized relationships among variables. PLS-SEM was chosen for its suitability in handling complex models with mediating and moderating effects and its robustness with smaller samples and non-normal data (Hair et al., 2012). Unlike traditional covariance-based SEM, which emphasizes model fit, PLS-SEM focuses on prediction and variance explanation, making it ideal for exploring behavioral outcomes such as user satisfaction and interaction with mobile healthcare technologies. This approach provides deeper insights compared to prior studies that relied on simpler regression analyses. The analysis was conducted in two phases: measurement model assessment and structural model assessment. The measurement model was tested by evaluating indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Reliability and validity were measured by calculating Cronbach's alpha, composite reliability, and average variance extracted (AVE). The Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio were used to check the discriminant validity. After validating the measurement model, the structural model was evaluated to examine the hypothesized relationships between constructs. Bootstrapping using 5,000 resamples was used to produce path coefficients, t-statistics, and p-values to ascertain the significance of the hypothesized paths. SmartPLS also performed mediating and moderating analyses to test the conceptual framework proposed, the mediating position of UT, and the moderating position of TR.

4. RESULTS

Table 1 and Figure 2 show that the reliability and validity analysis results of the constructs involved in the study are comprehensive. All constructs demonstrate high reliability, as evidenced by Cronbach's alpha and composite reliability (CR) values exceeding the recommended threshold of 0.70. For example, information quality achieved a Cronbach's alpha of 0.848 and a CR of 0.908, while personalization recorded an alpha of 0.882 and a CR of 0.927, both indicating strong internal consistency. Perceived ease of use also showed robust reliability with an alpha of 0.890 and a CR of 0.924, supported by high outer loadings of all four items above 0.84. Although security and privacy had slightly lower loadings, with one item (PS1) at 0.675, they remained adequately reliable with an alpha of 0.770 and a CR of 0.854. Constructs such as perceived usefulness, technology readiness, user interaction, user satisfaction, and user trust all met the reliability benchmarks, with outer loadings mostly above 0.70 and average variance extracted (AVE) values exceeding the cutpoint of 0.50, indicating sufficient convergent validity. For instance, personalization and information quality had AVE values of 0.809 and 0.767, respectively, demonstrating good construct validity. These findings confirm that the measurement model is both valid and reliable for subsequent analysis.

Table 1. Variables' reliability and validity.

Constructs	Items	Outer loading	Cronbach's alpha	CR	AVE
Information quality	IQ1	0.896	0.848	0.908	0.767
	IQ2	0.885			
	IQ3	0.844			
Personalization	P1	0.911	0.882	0.927	0.809
	P2	0.876			
	P3	0.912			
Perceived ease of use	PEU1	0.880	0.890	0.924	0.753
	PEU2	0.845			
	PEU3	0.893			
	PEU4	0.851			
Privacy and security	PS1	0.675	0.770	0.854	0.595
	PS2	0.775			
	PS3	0.841			
	PS4	0.787			
Perceived usefulness	PU1	0.898	0.900	0.927	0.717
	PU2	0.869			
	PU3	0.879			
	PU4	0.846			
	PU5	0.731			
Technology readiness	TR1	0.847	0.794	0.879	0.708
	TR2	0.859			
	TR3	0.819			
User interaction	UI1	0.732	0.850	0.899	0.692
	UI2	0.852			
	UI3	0.832			
	UI4	0.902			
User satisfaction	US1	0.842	0.807	0.885	0.720
	US2	0.877			
	US3	0.826			
User trust	UT1	0.650	0.781	0.860	0.608
	UT2	0.856			
	UT3	0.800			
	UT4	0.799			

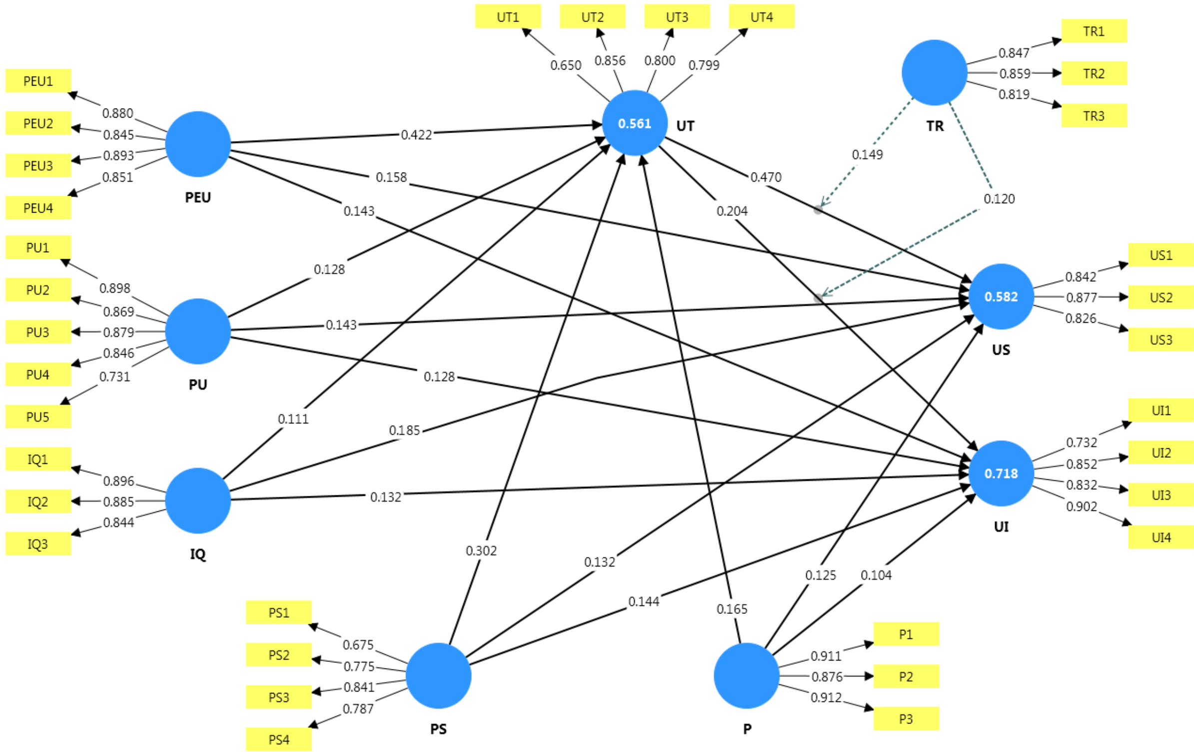

Figure 2. Estimated model.

Table 2 presents the discriminant validity test results based on the Fornell-Larcker criterion. The values along the diagonal, which are the square roots of the AVE, are greater than the inter-construct correlations, indicating good discriminant validity. For example, personalization reveals a diagonal value of 0.816, which is larger than its correlations with information quality (0.591) and perceived ease of use (0.816), establishing that personalization is empirically distinct. Similarly, perceived usefulness shows a high association with information quality (0.855) and perceived ease of use (0.805), but its discriminant validity remains intact since the diagonal values are larger than these correlations. Privacy and security also demonstrate distinctness, even as they report moderate correlations with user interaction (0.794) and user trust (0.791). Technology readiness shows its specificity, with a diagonal value of 0.732 that exceeds correlations with constructs like personalization (0.589) and information quality (0.489). User interaction, user satisfaction, and user trust all exhibit satisfactory discriminant validity, as their diagonal values surpass correlations with other constructs. These findings affirm that all constructs independently measure unique concepts, validating the strength of the measurement model.

Table 2. Discriminant validity.

Constructs	IQ	P	PEU	PS	PU	TR	UI	US	UT
Information quality									
Personalization	0.591								
Perceived ease of use	0.642	0.816							
Privacy and security	0.591	0.613	0.693						
Perceived usefulness	0.855	0.738	0.805	0.576					
Technology readiness	0.489	0.589	0.633	0.767	0.472				
User interaction	0.488	0.569	0.655	0.791	0.487	0.732			
User satisfaction	0.420	0.486	0.538	0.707	0.457	0.819	0.837		
User trust	0.618	0.769	0.846	0.794	0.664	0.774	0.828	0.842	

Table 3 presents the explanatory power of the structural model is demonstrated by R-square and model fit indicators. User interaction yielded the highest R-square measure of 0.718 (adjusted 0.710), indicating that more than 71 percent of interaction variance is predicted by the independent variables, which reveals a good level of predictive accuracy. User satisfaction had an R-square of 0.582 (adjusted 0.570), showing that more than half of the satisfaction variance is predicted by the independent variables. User trust also demonstrated considerable explanatory power with an R-square value of 0.561 (adjusted 0.553). All the predictive relevance statistics (Q^2predict) were positive and substantial, at 0.679 for user interaction, 0.450 for user satisfaction, and 0.539 for user trust, thus validating the predictive validity of the model. Goodness-of-fit statistics further confirm the strong fit of the model, with SRMR at 0.080, within the acceptable range of 0.08, and error statistics (RMSE and MAE) within tolerable levels. Taken together, these findings confirm that the structural model has strong explanatory and predictive strength for user trust, satisfaction, and use of mobile healthcare technology.

Table 3. R-square statistics model goodness of fit statistics.

Constructs	R-square	R-square adjusted	Q^2predict	RMSE	MAE	SRMR
User Interaction	0.718	0.710	0.679	0.571	0.446	0.080
User Satisfaction	0.582	0.570	0.450	0.747	0.567	
User Trust	0.561	0.553	0.539	0.684	0.557	

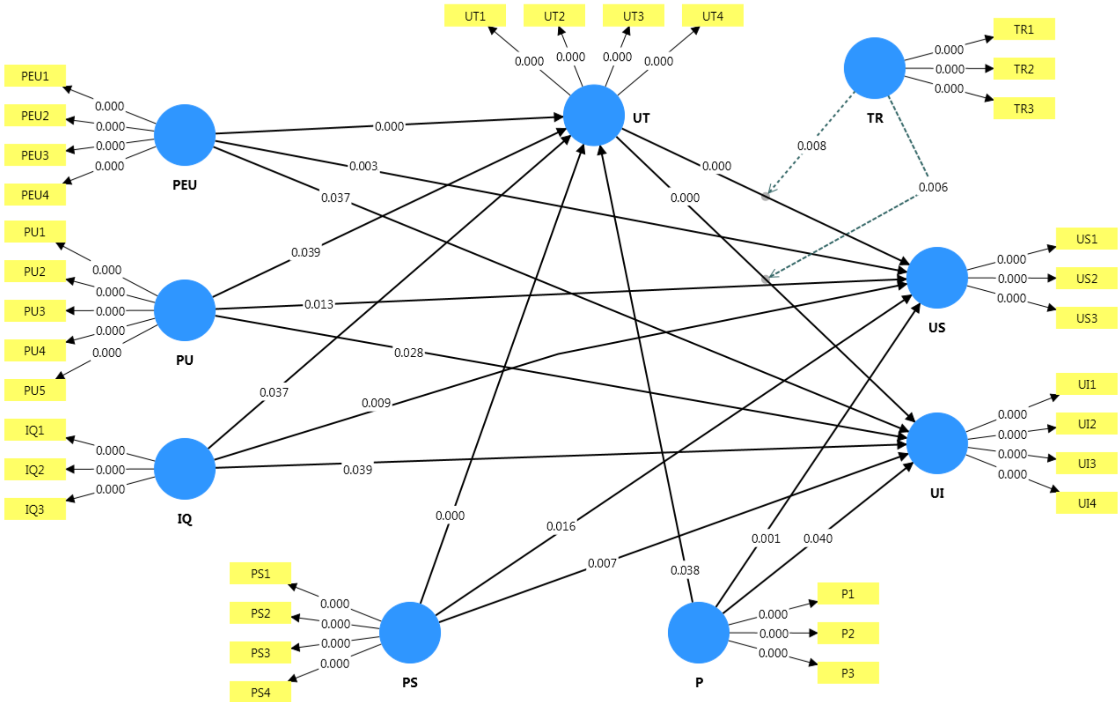

Figure 3. Structural model for path analysis.

Table 4 and Figure 3 summarize the results of hypothesis testing through path analysis, indicating that all proposed relationships were significant, as reflected by p-values less than 0.05 and t-statistics greater than 1.69. For direct effects, perceived ease of use (β = 0.158, p = 0.003), perceived usefulness (β = 0.143, p = 0.013), information quality (β = 0.185, p = 0.009), privacy and security (β = 0.132, p = 0.016), and personalization (β = 0.125, p = 0.038) all had positive impacts on user satisfaction. Likewise, these factors also significantly impacted user interaction, with values ranging from 0.104 to 0.144 and statistically significant p-values. Mediation effects of user trust were also present, validating that trust is a critical mechanism connecting system attributes with user satisfaction and user interaction. For example, the relationship from perceived ease of use through trust to satisfaction (β = 0.198, p < 0.001) was the highest among mediating effects, followed by privacy and security through trust to satisfaction (β = 0.142, p < 0.001). Mediating effects on interaction also existed at significant levels, with trust providing a link between the effects of perceived usefulness, information quality, and personalization on interaction. The analysis of moderation showed that technology readiness moderated the association between user trust and user satisfaction (β = 0.149, p =

0.008) and user interaction (β = 0.120, p = 0.006) positively, as hypothesized, supporting the strengthening effect. The path analysis as a whole strongly supports the conceptual model, demonstrating solid direct, mediating, and moderating associations among the constructs.

Table 4. Path analysis.

Paths	Original sample	T statistics	P-Values
PEU -> US	0.158	3.038	0.003*
PU -> US	0.143	2.215	0.013*
IQ -> US	0.185	2.721	0.009*
PS -> US	0.132	2.144	0.016*
P -> US	0.125	2.083	0.038*
PEU -> UI	0.143	1.789	0.037*
PU -> UI	0.128	2.169	0.028*
IQ -> UI	0.132	2.750	0.009*
PS -> UI	0.144	2.480	0.007*
P -> UI	0.104	1.756	0.040*
PEU -> UT -> US	0.198	3.710	0.000*
PU -> UT -> US	0.116	2.320	0.021*
IQ -> UT -> US	0.052	1.734	0.041*
PS -> UT -> US	0.142	4.043	0.000*
P -> UT -> US	0.095	2.021	0.044*
PEU -> UT -> UI	0.086	2.642	0.004*
PU -> UT -> UI	0.073	2.607	0.009*
IQ -> UT -> UI	0.064	2.065	0.039*
PS -> UT -> UI	0.062	2.718	0.003*
P -> UT -> UI	0.058	2.148	0.032*
TR x UT -> US	0.149	2.709	0.008*
TR x UT -> UI	0.120	2.791	0.006*

Note: * $p<0.05$.

5. DISCUSSION

The rapid advancement of mobile healthcare technologies has transformed how individuals access, manage, and interact with health-related services. The interpretation of user perceptions and engagement has become critical. With the development of these platforms into real-time health tracking, personalized guidance, and reliable interaction with medical professionals, perceptions of usability, usefulness, information quality, trust, and personalization have become primary considerations in the acceptance and subsequent involvement (Davis, 1989; DeLone & McLean, 2003; Venkatesh, 2000). At the same time, personal disparities in technology readiness influence the degree to which positive perceptions and trust translate into actual actions. Therefore, it is necessary to conduct a comprehensive analysis of both system features and user characteristics to understand the factors affecting user engagement and trust in mobile healthcare technologies.

The hypothesis H1a to H1e results show that all five system characteristics, PEU, PU, IQ, privacy and security, and personalization, have significant positive impacts on user satisfaction with mobile healthcare technologies. The correlation between PEU and satisfaction (H1a) confirms the initial hypothesis of the Technology Acceptance Model (TAM), which states that an easy-to-navigate system with minimal effort requirements positively impacts user attitude and evaluation, thereby increasing satisfaction (Davis, 1989; Venkatesh, 2000). Similarly, the significant influence of PU on satisfaction (H1b) supports the idea that users are more satisfied with technologies they perceive as improving their health management capabilities, aligning with the utilitarian focus of TAM on positive appraisals. Additionally, the positive impact of IQ on user satisfaction (H1c) aligns with the Information Systems Success Model (ISSM), indicating that relevant, accurate, and timely information enhances user confidence and system evaluation (DeLone & McLean, 2003). One of the most important determinants was privacy and security (H1d), which suggests that the protection of personal health information leads to trust, and subsequently to better satisfaction, supporting trust-based attitudes towards the adoption of technologies (Dhote et al., 2023). Last but not least, personalization (H1e) has a positive influence on satisfaction, and adaptive content and custom features make it more valuable and relevant, which positively influences the overall assessment of the system by the user (Kitsios et al., 2023). All these findings suggest that the perception of mobile healthcare technologies as satisfying depends on usability, utility, the reliability of the presented information, security, and user-centered features, which, in turn, underscore the importance of an integrated approach to designing healthcare platforms.

In the cases of H2a to H2e, the findings indicate that PEU, PU, IQ, privacy and security, and personalization also play a major positive role in UI with mobile healthcare technologies. PEU (H2a) was significantly linked to interaction, indicating that the simplified system design facilitates active user interaction with features and exploration of functions, consistent with TAM principles that ease of use triggers behavioral engagement (Davis, 1989; Venkatesh, 2000). PU (H2b) also amplified interaction, implying that users tend to interact with systems they consider helpful in managing their health, aligning with the utility-based behavioral approach to TAM. Interaction was also positively correlated with IQ (H2c), reflecting the ISSM claim that high-quality information stimulates repeated and meaningful use by making users more confident in their decision-making (DeLone & McLean, 2003). The interaction was reinforced by privacy and security (H2d), where trust in data protection mechanisms reduces perceptions of risks and encourages active interaction, supporting theories of trust-based adoption (Gefen et al., 2003). Lastly, the concept of personalization (H2e) has a positive effect on interaction, meaning that the relevance and perceived usefulness of the system can increase when it provides tailored recommendations, adaptive feedback, and personalized content, which also makes users more willing to engage with the system (Liu et al., 2023). On the whole, these findings demonstrate that mobile healthcare platform UI is affected not only by system functionality and IQ but also by trust and customized experiences, which are consistent with the integrated theoretical frameworks that merge TAM, ISSM, and trust-based points of view.

The findings on the hypotheses H3a to H3e indicate that UT has an important mediating role in the relationships between PEU, PU, IQ, privacy and security, and personalization, and the US with mobile healthcare technologies. In particular, the positive influences of system characteristics on satisfaction are enhanced when mediated by trust, and it is most important that trust, as a psychological process, connects users' perceptions of the technology with the outcomes of their evaluation. The results align with extensions of the TAM, which propose that, although PEU and PU directly affect attitudes and satisfaction, the development of trust is often an intermediary to be used in sensitive settings like healthcare, where users need to be confident that the system can handle personal health data of individual recipients accurately and safely (Davis, 1989; Venkatesh, 2000). Similarly, the ISSM supports these results by emphasizing that high-quality, accurate, and relevant information increases confidence in the system, which subsequently fosters trust and enhances satisfaction (Joshua et al., 2023). The mediating effect of trust is also reinforced by trust-based perspectives in technology adoption, which argue that users' confidence in privacy, security, and the reliability of personalized features strengthens their positive evaluation of the system (Cao et al., 2024). For example, while personalization enhances the perceived relevance of content, users may only experience heightened satisfaction when trust assures them that their personal information is handled responsibly and that the recommendations are credible. Overall, these results indicate that trust functions as a critical conduit through which system characteristics translate into user satisfaction, providing empirical support for integrated models that combine TAM, IS Success Model, and trust-based theories in healthcare technology adoption.

For hypotheses H4a through H4e, the findings demonstrate that UT also mediates the relationships between PEU, PU, IQ, privacy and security, and personalization, and UI with mobile healthcare technologies. The results suggest that while these system characteristics positively influence interaction, the effect is amplified when users trust the system, highlighting the importance of trust in facilitating behavioral engagement with digital health platforms. Theoretically, this aligns with the extensions of TAM that incorporate post-adoption behaviors, suggesting that even if a system is easy to use or useful, users' interaction is contingent on their confidence in the system's reliability and security (Davis, 1989; Venkatesh, 2000). The mediation of trust is also supported by the ISSM, as high-quality information and accurate system functionality create trust that encourages more frequent and meaningful engagement with the technology (Tenggono et al., 2024). Trust-based perspectives further explain that users are more likely to explore features, provide feedback, and engage in repeated use when privacy, security, and personalization reinforce their confidence in the system (Ali et al., 2024). For instance, secure and privacy-compliant mobile healthcare applications reduce perceived risks and allow users to interact without hesitation, while personalized features tailored to health needs strengthen trust-driven engagement. These findings highlight the centrality of trust in converting favorable system perceptions into active interaction behaviors, confirming that trust is both a psychological and behavioral mediator in mobile healthcare technology adoption, thereby integrating TAM, IS Success, and trust-based theoretical perspectives into a cohesive explanatory framework.

The findings for hypotheses H5a and H5b indicate that TR significantly moderates the relationships between UT and both US and UI, such that these relationships are stronger when users exhibit higher levels of TR. This suggests that individuals who are more optimistic, innovative, and confident in their ability to use new technologies are better able to translate trust in mobile healthcare systems into positive outcomes. From the perspective of the TAM and its extensions, TR can be understood as an individual difference factor that amplifies the effects of trust on post-adoption behaviors, reinforcing the notion that users' predispositions toward technology influence the degree to which perceived system reliability and usefulness lead to satisfaction and engagement (Davis, 1989; Venkatesh, 2000). In line with the ISSM, users with higher TR are more likely to leverage high-quality information, privacy-protected features, and personalized functionalities to enhance their satisfaction and actively interact with the system, as their readiness reduces anxiety and increases confidence in navigating complex or novel digital platforms (Kim, 2024). This interpretation is also supported by trust-based perspectives, which highlight that trust does not necessarily result in full satisfaction or interaction among less comfortable or more experienced users with technology, but high readiness converts trust to behavioral engagement (Zhan et al., 2024). This empirically suggests that TR is an important boundary condition, reinforcing the positive role of UT on cognitive and behavioral outcomes in the implementation of mobile health, and therefore, developers and health practitioners need to consider user readiness when developing and marketing digital health interventions to achieve optimal satisfaction and long-term engagement.

On the whole, the results of this research present good empirical evidence for the integrated theoretical framework as it proves that system characteristics, trust, and TR are the combined factors that influence US and the interaction with mobile healthcare technologies. PEU, PU, IQ, privacy and security, and personalization not only directly influence satisfaction and interaction but also exert indirect effects through the mediating role of trust, while TR strengthens the impact of trust on outcomes. These results underscore the value of combining the TAM, the ISSM, and trust-based perspectives to understand user engagement in sensitive and complex technology domains. Practically, the study highlights that developers and healthcare providers must focus on designing intuitive, useful, reliable, and personalized systems while fostering trust and accounting for user readiness to ensure optimal adoption, satisfaction, and engagement. Collectively, this research contributes to both theory and practice by providing a nuanced understanding of the cognitive, psychological, and behavioral processes underlying mobile healthcare technology use.

6. IMPLICATIONS

6.1. Practical Implications

The findings of this study offer several practical implications for developers, healthcare providers, and policymakers seeking to enhance the adoption, satisfaction, and engagement of users with mobile healthcare technologies. First, the findings highlight the significance of creating user-friendly interfaces and well-organized navigation to improve perceived ease of use (PEU), as simplifying interactions can significantly increase satisfaction and active participation. Second, emphasizing features that help users manage their health, such as symptom tracking, medication reminders, and real-time interaction with healthcare professionals, can reinforce the perceived usefulness of the system and promote continued use. Third, ensuring that the information provided is of high quality, accurate, and timely is essential because information quality (IQ) directly influences trust and user engagement, which in turn leads to better health-related decision-making. Fourth, developers must focus on maintaining high privacy and security standards to protect sensitive health information, thereby reducing user anxieties and building trust, which results in increased interaction and satisfaction. Lastly, incorporating more individualization features that align with personal health demands, preferences, and behaviors can create more relevant and engaging user experiences, ultimately increasing adherence to digital health interventions. Additionally, understanding users' trust (TR) enables organizations to stratify and customize strategies, such as tailored onboarding or tutorials, to maximize satisfaction, trust, and interaction. These perspectives provide practical guidance on developing mobile healthcare technologies that meet user expectations, foster trust, and facilitate meaningful communication.

6.2. Theoretical Implications

This study significantly advances the theoretical understanding of the interaction between the US healthcare system and mobile healthcare technologies by integrating the Technology Acceptance Model (TAM), the Information Systems Success Model (ISSM), and trust-based perspectives. It extends traditional TAM constructs within the healthcare context by demonstrating that perceived ease of use (PEU), perceived usefulness (PU), information quality (IQ), privacy and security, and personalization directly influence user outcomes, thereby emphasizing their importance in high-stakes, sensitive environments. The mediating role of UT empirically supports trust-based adoption theories, highlighting that psychological trust in system reliability and security is a crucial process linking system features to both cognitive and behavioral consequences. Furthermore, the moderating effect of TR enhances understanding of individual differences in technology adoption, indicating that user tendencies toward innovation and online presence amplify the influence of trust on user satisfaction and interaction. Through these theoretical frameworks, the study offers a comprehensive model that encompasses cognitive, affective, and behavioral aspects of mobile healthcare technology use, addressing gaps in previous research that often examined these aspects in isolation. This integrated model contributes valuable insights to the literature, providing a robust explanation of the complex processes involved in technology adoption and user engagement in digital health environments.

7. LIMITATIONS AND FUTURE DIRECTIONS

7.1. Limitations

Although this research has yielded worthwhile insights, the study has a number of limitations that should be taken into account when interpreting the findings. To begin with, the study was based on a cross-sectional survey design, which restricts the possibility of concluding cause-and-effect relationships between the constructs, as data were gathered at one point in time. Second, the sample was selected among users of mobile healthcare technologies in China by a purposive technique that can influence the applicability of the findings to other contexts of culture and healthcare. Third, the research used self-reported variables, which can lead to common method bias and might reflect subjective perceptions rather than real behavioral patterns. Also, although important system characteristics, trust, and TR were included, other possible variables that may have played a role in the study, such as social influence, organizational support, or health literacy, were omitted. Such constraints imply that the results must be interpreted with caution and that it is advisable to replicate such studies in other settings and employ different research designs to strengthen the findings.

7.2. Future Research Directions

The current study could be expanded in future research by filling in the gaps found in the study and expanding the scope to cover other aspects of the adoption of mobile healthcare technology. The cause-and-effect relationships and the dynamic changes between the US, UT, and interaction could be studied using longitudinal studies to offer a deeper understanding of post-adoption behaviors. It would be better to extend the study to cover various populations from different countries and healthcare regimes to increase the generalizability of the results and provide cross-cultural comparisons. Other constructs might also be added in further research, including social influence, perceived risk, health literacy, and digital engagement strategies, to create a well-rounded view of the factors affecting US and interaction. Lastly, the use of mixed-method techniques, including surveys and qualitative interviews or behavioral analytics, would yield more comprehensive data on user experiences and decision-making, which in turn would be used to create more efficient and user-centered mobile healthcare technologies.

8. CONCLUSION

The current research provides a comprehensive insight into the influences of user satisfaction and engagement with mobile healthcare technologies. It finds that perceived ease of use, perceived usefulness, information quality, privacy and security, and personalization significantly impact users' satisfaction. The findings affirm that user trust is an essential psychological link between technological perceptions and user outcomes, with technology readiness reinforcing these relationships. The study integrates the Technology Acceptance Model, the Information Systems Success Model, and trust-based perspectives, forming a robust theoretical framework for understanding user behavior in electronic health settings. Politically and socially, these findings have noteworthy implications for healthcare administrators, public health authorities, and digital health program designers. They suggest that user trust, technological inclusiveness, and data protection should be central to national and institutional digital health strategies to promote equitable access and involvement. These insights can inform the development of frameworks that ensure ethical data management, increase digital literacy, and improve preparedness across diverse population groups, thereby reducing disparities in technological adoption. Additionally, health administrators can leverage these results to develop more patient-centered systems that enhance satisfaction, improve healthcare delivery, and foster preventive health actions with sustained engagement on digital platforms. Consequently, this study is relevant not only to academic discussions on technology adoption but also to societal efforts to harness mobile healthcare technologies as transformative tools for improving healthcare accessibility, efficiency, and population well-being.

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Institutional Review Board Statement: This study was approved by the Ethics Committee of Universiti Sains Malaysia (JEPeM-USM) under protocol number (IRB No. USM/JEPeM/PP/240101024), dated October 4, 2024. Informed verbal consent was obtained from all participants, and all data were anonymized to protect participant confidentiality.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
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