Global Journal of Health Science; Vol. 16, No. 5; 2024
ISSN 1916-9736 E-ISSN 1916-9744
Published by Canadian Center of Science and Education

Social Acceptance of Mobile Health Technologies Among the Young Population in Nigeria

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Received: February 24, 2024 Accepted: April 18, 2024 Online Published: April 26, 2024

doi:10.5539/gjhs.v16n5p22 URL: https://doi.org/10.5539/gjhs.v16n5p22

Abstract

Mobile devices are widely used in modernizing healthcare delivery because of their unique features related to accessibility, virtual interaction, and connectivity. While developing countries, with limited resources, strive to achieve high healthcare standards, and mobile health (mHealth) solutions could transform healthcare delivery systems in these countries, their functionality is currently limited. This study investigates the potential systematic introduction of mHealth services and their social acceptability in developing countries, with a particular focus on Nigeria. This cross-sectional study was conducted with a sample of university students. Structural equation modeling was used to test the study hypotheses, and descriptive statistics were used to analyze the sociodemographic characteristics of the participants. Psychological and personal characteristics, environmental characteristics, and conditions of use associated with mHealth technology adoption were examined based on eight constructs (health consciousness, trust, social influence, perceived risk, performance expectancy, facilitating conditions, effort expectancy, and behavioral intention). The results indicate that trust and performance expectancy are significant predictors of mHealth acceptance in the surveyed population. The future acceptance of mHealth among young people in developing countries holds great significance for improving healthcare delivery, addressing the unique challenges faced by developing countries, and leveraging the preferences of young individuals, which could contribute to the advancement of mHealth solutions and enhance healthcare accessibility. The findings shed light on the acceptance of mHealth technologies among the young populations of developing countries, with implications for future efforts to improve healthcare delivery and address the healthcare challenges of these countries.

Keywords: mHealth, mobile health, developing countries, healthcare accessibility, digital divide, sociocultural factors, young population, healthcare delivery

1. Introduction

Social acceptance of mobile health (mHealth) among the young populations of developing countries is a crucial aspect to consider when implementing and expanding mHealth initiatives. In recent years, mHealth initiatives have gained traction as a means of providing healthcare services through mobile devices. The rapid development of information and communication technologies has opened enormous opportunities for healthcare, especially in developing countries where there is a shortage of healthcare professionals (Cao et al., 2022). In this context, mHealth applications and technologies have been noted for their potential to enhance healthcare delivery in resource-poor countries with shortages of healthcare professionals (Adetunji et al., 2021). Thus, social acceptance of mHealth among the young population of developing countries is of great significance in today's digital era. Access to quality healthcare is a fundamental human right and the cornerstone of social and economic development. However, in developing countries, the realization of this right remains a persistent and complex challenge (Ilozumba et al., 2018; Tian et al., 2017; Torres-Quintero et al., 2020). Nigeria, one of the developing countries in West Africa, is in the sub-Saharan Africa region and is the most populous nation in Africa. In Nigeria, an estimated 200 million people have health and medical histories linked to both traditional practices and modern (orthodox) healthcare systems; the latter as mainly established to serve the healthcare needs of the colonial administration and expatriate communities. There was a gradual shift post-independence—from 1960 onward—toward a more inclusive healthcare policy and a systematic healthcare approach, with investments in infrastructure, public health campaigns, and the establishment of hospitals and clinics (Aka & Balogun, 2022; Aregbeshola 2021; Scott-Emuakpor, 2010). This resulted in a health system approach segmented into primary, secondary, and tertiary levels of care (Figure 1). However, despite these efforts, the healthcare sector of the country is still consistently confronting various challenges, including a high incidence of diseases such as malaria and cholera, and an equally large number of cases of maternal and child deaths (Omoleke & Taleat, 2018). The system also faces challenges due to the lack of adequate infrastructure and qualified medical professionals (Oleribe et al., 2019). Addressing the complex challenges within Nigeria's healthcare system, which include the critical shortage of healthcare professionals and limited access to medical facilities in rural areas, mHealth technologies offer targeted solutions that harness the widespread use of mobile devices. Specifically, mHealth initiatives, such as telehealth services and mobile health information platforms, have the potential to bridge the gap in healthcare access. They enable remote consultations and health monitoring, thereby circumventing the logistical constraints of traditional healthcare delivery methods. Moreover, mHealth applications can facilitate disease tracking and health education, directly addressing issues of disease prevalence and public health awareness. This study visualizes the aforementioned mHealth interventions, assessing their capacity to tackle the acknowledged healthcare obstacles and examining their reception among the youth population in Nigeria.

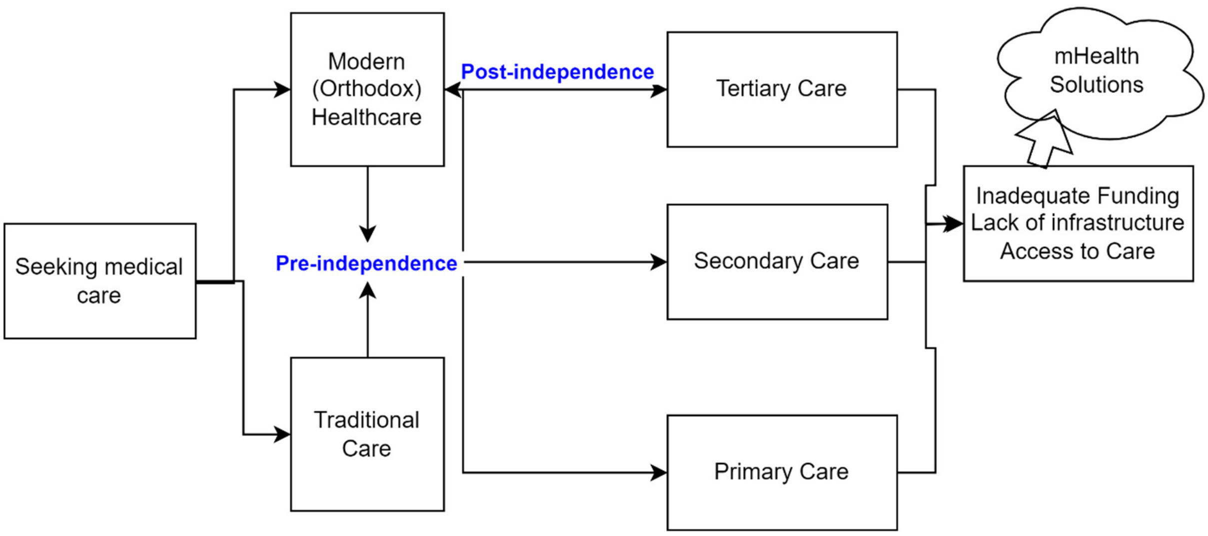

Figure 1. Nigeria’s health system approach: Pre- and post-independence

The steps being taken to transform and augment healthcare delivery are evidenced by recent developments such as the National Health Insurance Scheme (NHIS) and public health programs focusing on polio and malaria, to name a few (Effiong et al., 2023; Gbolahan & Oyeranmi, 2023). However, funding issues, management inefficiencies, and uneven resource distribution continue to plague the system. In such an environment, mHealth technologies emerge as a potentially viable solution to some of these persistent problems. The current estimates of smartphones users in Nigeria are between 25 and 40 million, and it is projected to exceed 140 million by year 2025 (*Smartphone Users in Nigeria 2014-2025 | Statista, 2023*). Taking advantage of the fast rate and widespread nature of mobile phone use in Nigeria with over 32 percent penetration annual growth rate (Aimuengheuwa, 2023), particularly among the young generation between 18 to 40 years who represent over 70 percent of the population, mHealth has great potential to help transform healthcare provision by increasing access to medical information, enabling remote diagnosis where needed, and facilitating the efficient management of health services, particularly among people living in far-flung areas. The use of mHealth applications in developing countries holds promise for improving healthcare access and outcomes for individuals with limited access to healthcare facilities and services

(Tudor et al., 2022). However, there exists a lack of comprehensive understanding regarding how exactly mHealth can systematically address these challenges, as well as whether it will be socially acceptable within the Nigerian context. This study aims to fill this notable gap by examining the potential of mHealth in mitigating specific healthcare delivery issues in Nigeria and exploring the factors that influence its acceptance among young populations. Hence, our research problem centers on the exploration of how mHealth solutions can be optimized to effectively overcome the identified healthcare system challenges, while also considering the extent to which they will be embraced by Nigeria's youth population. This research utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) as a theoretical framework. The UTAUT combines principles from eight different theories in social and psychological disciplines (Venkatesh et al., 2003). This comprehensive framework outlines the various factors that influence technology adoption, which is essential for understanding the complexities surrounding the acceptance of mHealth. It enables the examination of the interplay between technological, psychological, and social factors that significantly impact the willingness to accept and future utilization of mHealth technologies among the young population.

1.1 Definition of mHealth

mHealth refers to the use of mobile technology such as smartphones and tablets in the provision of healthcare services and information (Karlyn et al., 2020). The World Health Organization (WHO) defines mHealth as the practice of medicine and public health supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices (Sakina et al., 2023). In addition, mHealth encompasses the use of mobile and wireless technologies to support the achievement of health objectives, providing health information and services through smartphones (Torres-Quintero et al., 2020). In the modern era, burgeoning interest in mHealth, particularly among young adults in technologically advanced countries such as Japan, has garnered the attention of researchers and healthcare professionals alike (Hu et al., 2022). Indeed, mHealth technology has been widely adopted in numerous countries, with the potential to significantly improve patients' compliance with treatment and aid them in managing their health by providing access to medical services from the comfort of their homes. One of the primary concerns associated with reliance on mHealth technologies in developing countries pertains to the digital divide. Despite the increasing penetration of mobile phones in these regions, disparities in access to smartphones and reliable internet connectivity persist. Consequently, the universality of mHealth applications may be limited by socioeconomic and infrastructural barriers, potentially exacerbating existing health inequities within these communities (Rahman et al., 2021).

Meanwhile, mHealth initiatives have been instrumental in extending the reach of healthcare services to remote and underserved areas, thereby bridging the gap between healthcare providers and patients (Tian et al., 2017). In addition, mHealth encompasses a wide range of services and applications, including remote patient monitoring, disease surveillance, health promotion, and information dissemination (Karlyn et al., 2020). In the context of this research, mHealth technology constitutes tools for improving the quality of healthcare provision and creating equal opportunities for healthcare in under-resourced areas, particularly in developing countries. The widespread availability of mobile phones and the increasing penetration of mobile technology make mHealth a promising tool for addressing healthcare challenges in developing countries (Swanepoel, 2017). This rapid increase in smartphone penetration has shown the potential for addressing healthcare challenges in low- and middle-income countries, where access to traditional healthcare services may be limited. Furthermore, the widespread adoption of mobile phones and communication technologies would contribute to empowering patients to actively manage the health issues they experience and the related risk factors.

1.2 Mobile Health in Developed and Developing Countries

In both developed and developing countries, mHealth technology has emerged as a transformative force (Karlyn et al., 2020), offering innovative solutions to enhance healthcare accessibility and delivery. Rapid advances in mobile technologies and applications, coupled with continued growth in the coverage of mobile cellular networks, have driven a transformative shift toward the utilization of mHealth applications in healthcare. In developed countries, substantial investments have been made to enhance healthcare access through mHealth initiatives; remote consultations and monitoring of chronic conditions have become possible in these countries due to mHealth technology (Shen et al., 2017). Meanwhile, the acceptance and adoption of mHealth initiatives in developing countries have encountered challenges. For instance, in Nigeria (Eze et al., 2022), socio-economic and cultural factors have been found to be pivotal in integrating mHealth into healthcare systems. As such, these nations are uncovering the intricate dynamics of mHealth acceptance and acknowledging the profound influence of cultural, economic, and technological elements. Countries such as India have witnessed a surge in mHealth initiatives, with studies indicating that perceived usefulness, ease of use, and trust significantly influence acceptance. The affordability and accessibility of mobile technology also play a crucial role in the positive reception of mHealth services (Rajak & Shaw, 2021). In the context of Africa, the promise of mHealth has been recognized in South Africa, particularly in rural areas. The acceptance of mHealth in South Africa is influenced by factors similar to those in other regions, with an additional focus on privacy and security concerns (Van Der Pol et al., 2021). In Uganda, mHealth interventions targeting healthcare challenges (e.g., associated with maternal and child health) have also underscored the importance of mHealth in addressing digital literacy and infrastructure limitations (Palos-Sanchez et al., 2021; Takuwa et al., 2023). Nonetheless, mHealth has significant potential to address various healthcare challenges in developing countries despite the associated drawbacks that may limit its acceptance (Adcock et al., 2022).

1.3 Research Objectives

This study aimed to examine the social acceptability of mHealth among young populations in developing nations. Specifically, our focus was on understanding the factors that can contribute to the acceptance of mHealth tools among young individuals, who represent future consumers, compared to older demographics. This study drew inspiration from prior research offering valuable insights into the complexities surrounding the adoption of mHealth technology. For example, Alam et al. (2020) examined the factors affecting the adoption of mHealth services as well as the moderating effect of gender on the intention to use and the actual usage behavior of users of mHealth services; their results revealed that performance expectancy, social influence, facilitating conditions, and perceived reliability were found impacting the adoption of mHealth solutions in developing countries such as Bangladesh. Further, Alaiad et al. (2019) grounded their analysis in established models of technology acceptance, revealing a strong association between various factors, including performance, effort, and social influence, as well as the intention to use mHealth. They also noted the negative impacts of security and privacy concerns on such intentions. Karaegeorgos et al. (2019) synthesized findings from multiple studies to highlight the potential advantages of mHealth in improving healthcare systems in resource-limited settings in developing countries. Nevertheless, the specific sociocultural and economic factors influencing mHealth adoption in developing nations, from the perspective of prospective users' behavioral intention, remain unclear. Addressing this gap in prior knowledge is crucial for developing a strategy for mHealth social integration that aligns with developing nations' unique needs and ensuring its sustainability and effectiveness in these countries.

1.4 Significance of the Study

It is imperative to explore and address the specific social, cultural, and economic determinants that affect the acceptance, adoption, and use of mHealth technologies in developing countries. By doing so, we can tailor mHealth initiatives to the unique needs and preferences of the young population in developing countries, thereby enhancing the accessibility, affordability, and effectiveness of healthcare services. This need is particularly highlighted in the context of patients' acceptance of and willingness to use mHealth technologies in developing countries. As mHealth has gained attention as a form of technology effective for solving healthcare-related challenges, studying the social acceptance of mHealth among young populations in developing countries would help bridge the gaps in extant literature on health outcomes and the adoption of mHealth apps in global populations; in this regard, it is essential to further explore the socioeconomic and cultural factors that influence the use of these technologies (Palos-Sanchez et al., 2021). The unique needs and preferences of the young populations of developing countries call for a comprehensive understanding of the factors influencing the adoption of mHealth services. Although the potential of mHealth to transform healthcare services in developing countries is evident, its successful integration into healthcare ecosystems hinges on a multifaceted understanding of the factors influencing its social acceptance. As the adoption of mHealth is gaining traction in Nigeria, it is imperative to comprehend user perceptions influenced by socioeconomic and cultural determinants. This study, involving an undergraduate student population, sheds light on the facilitating or impeding factors related to health behavior, access, and quality healthcare services, specifically clarifying how mHealth impacts healthcare delivery within this demographic. The study is significant as it presents insights that could guide the development of tailored strategies and optimized solutions specific to young populations in developing countries; this could in turn promote equitable healthcare delivery through improved health outcomes, pave the way for broadening healthcare access, and foster a more transformative impact with respect to healthcare outcomes across diverse populations. The unique needs and preferences of the population in developing countries call for a comprehensive understanding of the factors influencing mHealth adoption (Namirad, 2023). Underscoring the multidimensional nature of mHealth acceptance in developing countries, driven by cultural, economic, and technological factors, is important to determine the barriers and challenges (e.g., associated with privacy and health literacy) that need to be addressed for successful implementation. These insights could provide a foundational understanding of the complex interplay of factors that may influence the social acceptance of mHealth services, which is essential for guiding the adoption of mHealth services among young populations. Further, they could contribute to the existing body of knowledge by presenting a scholarly framework for understanding how specific factors can impact the social acceptance and future adoption of mHealth services.

1.5 Adapted Research Model and Hypotheses

This study employed an adapted version of the Unified Theory of Acceptance and Use of Technology (UTAUT) model used by Cao et al. (2022) in their study (Figure 2). The UTAUT model, originally proposed by Venkatesh et al. (2003), is a widely used framework for understanding the factors that influence the acceptance and use of technology. This model combines several other theories, including the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model, the Theory of Planned Behavior (TPB), a combined TAM and TPB model, the Model of PC Utilization, the Innovation Diffusion Theory (IDT), and the Social Cognitive Theory (SCT). These theories provide a framework for understanding and predicting individual behaviors and attitudes toward technology adoption and usage. For our study, we utilized the model expanded by Cao et al. (2022) with the inclusion of three additional constructs to the original UTAUT structure: health consciousness, perceived risk, and trust. Cao et al.'s (2022) model comprises four aspects—Psychological Dimension, including Personal Characteristics, Environmental Characteristics, and Conditions of Use—and eight constructs—Health Consciousness (HC), Trust (TR), Social Influence (SI), Perceived Risk (PR), Performance Expectancy (PE), Facilitating Conditions (FC), Effort Expectancy (EE), and Behavioral Intention (BI). This broadened framework enables a more detailed analysis of determinants linked to the adoption of and attitudes toward mHealth among the younger generation in Nigeria.

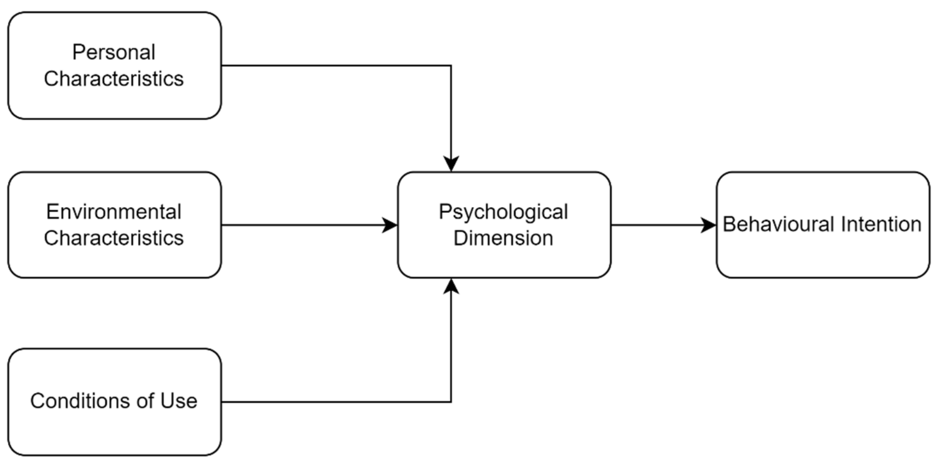

Figure 2. Adapted research model (Cao et al., 2022)

The study hypotheses are based on several relevant variables, as presented in Appendix A; these include perceived risk, trust, performance expectancy, effort expectancy, health consciousness, social influence, and facilitating conditions, each playing a crucial role in shaping user attitudes regarding and intentions to use mHealth services. Below, we briefly describe each of the variables.

Health Consciousness: This reflects the degree to which individuals are aware of their health status and concerned about their health. This is measured by asking how much attention is paid to one's health. Health consciousness has been reported to be correlated with a range of health-related behaviors (Acharya & Lee, 2022). Individuals with a heightened level of health consciousness reflect not only their physical condition but their overall well-being. Consequently, they tend to consider mHealth interventions as less risky.

Trust: Trust in mHealth services encompasses the elements of reliability, security, credibility, and user satisfaction. This is measured by asking if the questionnaire respondent trust technology providers or related personnels. High levels of trust in these services lead to a greater likelihood of their adoption and use among individuals seeking healthcare support (He, 2023).

Social Influence: In this study, social influence refers to the impact of societal and peer pressure on an individual's decision to use mHealth services (Alam et al., 2020). This is measured by asking if socially respected people would value technology services in interest. This encompasses endorsements from social circles and community opinions, which can significantly affect the adoption of mHealth services.

Perceived Risk: In the context of mHealth acceptance in this study, perceived risk refers to the concerns of an individual regarding privacy, data security, and any potential errors in the applications (Klaver et al., 2021). This is measured by asking if the questionnaire respondent is afraid of risks such as privacy violation or potential abuse by cyber criminals. When individuals perceive a higher level of risk associated with using these technologies, they are less likely to adopt and use them (Fan et al., 2018).

Performance Expectancy: This refers to individuals' confidence in the ability of mHealth services to assist them in meeting or achieving their healthcare needs and goals (Zhao et al., 2018). This is measured by asking if the questionnaire respondent feels technology can help one's activities. It includes individuals' trust in how effective and beneficial these services are for enhancing their general state of health and meeting health objectives.

Facilitating Conditions: This variable captures the degree to which an individual believes that organizational and technological infrastructure exists to support the use of mHealth services (Almegbel & Aloud, 2021). This is measured by asking if the questionnaire respondent has necessary resources to enable technology use. It highlights the importance of accessible and user-friendly mHealth platforms.

Effort Expectancy: In this study, effort expectancy refers to the level of simplicity of mHealth technologies, which can invariably influence an individual's intention to use mHealth services (Semiz & Semiz, 2021). This is measured by asking if the questionnaire respondent feels interaction with technology is easy, clear, and understandable. A higher level of effort expectancy can positively influence one's behavioral intention to use mHealth services (Almegbel & Aloud, 2021).

Based on these constructs, we formulated the following hypotheses:

- Perceived risk negatively affects behavioral intentions to use mHealth technologies (H1).
- Trust positively influences behavioral intentions to use mHealth technologies (H2).
- Performance expectancy positively affects behavioral intentions to use mHealth technologies (H3).
- Effort expectancy positively affects behavioral intentions to use mHealth technologies (H4).
- Health consciousness has a negative impact on perceived risk (H5a), a positive impact on trust (H5b), and a positive impact on perceived usefulness (H5c) related to mHealth technologies.
- Social influence has a negative impact on perceived risk (H6a), a positive impact on trust (H6b), and a positive impact on perceived usefulness (H6c) related to mHealth technologies.
- Facilitating conditions positively affect effort expectancy regarding mHealth technologies (H7).

2. Methodology

2.1 Research Design

We employed a quantitative research design. A cross-sectional survey was conducted to obtain information from a sample of undergraduate students from various universities in Nigeria, recruited using convenience sampling. The survey was administered through a Google Form to gather information about the participants' perceptions and attitudes regarding mHealth. The questionnaire was based on the methodological approach described by Cao et al. (2022) (Appendix B). It was designed to evaluate participants' level of awareness about and intention to use mHealth services, by integrating the constructs of Performance Expectation (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI) as conceptualized within the UTAUT model (Venkatesh et al., 2003). The items on Health Consciousness (HC) were based on Guo et al.'s (2020) study, those on Perceived Risk (PR) based on Deng et al.'s (2018) study, and those on Trust (TR) based on Farid et al.'s research (2020). We adapted these questionnaire items due to their uniqueness and relevance, which aligned with the objectives of this study. All items were rated on a 5-point Likert scale from 'Strongly Disagree' to 'Strongly Agree'. This study was conducted without the need for ethics review board approval. It is based on the absence of interventions, invasive procedures, or sensitive data collection.

2.2 Sample Size

Determining an appropriate sample size is crucial to ensure that the study findings are statistically reliable and can be generalized to the target population (Althubaiti, 2022). In this study, the sample size was calculated using the following formula: Z^2 * p * (1-p) / e^2, with a confidence level of 95% (Z = 1.645), a margin of error of 5% (E = 0.05), and estimated proportion (p) = 50% (0.5) (Bujang, 2023). This calculation yielded an approximate sample size of 270 respondents, aligning with accepted parameters for confidence levels and error margins (Bujang, 2023). However, owing to certain assumed research constraints, we initially targeted 250 respondents for our survey, and we received a total of 377 responses. Data cleaning was performed to ensure the quality and validity of the dataset. In this process, 39 responses with a variance less than 0.25 were excluded. Additionally, 54 duplicate entries and entries with missing or empty fields were excluded. This rigorous data-cleaning procedure resulted in our identification of 93 respondents with invalid entries, consequently excluded from the analysis. After data cleaning, we obtained a valid dataset of 284 respondents for subsequent analysis.

2.3 Data Collection

In this study, we used an online questionnaire developed using Google Forms to collect data. The questionnaire was distributed to undergraduate students from four universities in Nigeria. To facilitate widespread and efficient participation, links to the survey were shared through various social media platforms. Informed consent was obtained from the participants, only after which could they complete the questionnaire. Additionally, measures were taken to ensure the anonymity and confidentiality of respondents' information by removing any identifying details from the collected data. Data collection took place from December 2, 2022, to January 11, 2023, with a substantial number of responses received during this period that could be used for our data analysis. The online questionnaire was meticulously designed to prioritize participant privacy and avoid discussing sensitive topics. This emphasizes our commitment to ethical research practices, which align with the guidelines governing studies of this kind. The voluntary participation of all respondents, along with clear communication about the study's objectives and the confidentiality of their responses, was highly valued. Our adherence to these principles demonstrates a thorough examination of ethical standards, reinforcing the integrity of our study without necessitating formal ethics board review.

2.4 Data Analysis

Data analysis was conducted using SmartPLS 4, a robust software for structural equation modeling (SEM), enabling the exploration of relationships between variables and a more profound examination of the factors influencing the social acceptance of mHealth. Further, SPSS version 28 was used to perform descriptive analyses, enhancing the comprehensiveness of our approach. It revealed the socio-demographic profiles of the participants, including gender, age, education level, career, income, and mobile usage experience. This dual approach allowed for a comprehensive understanding of the data, with SmartPLS 4 focusing on the model's structural aspects and SPSS providing foundational insights into the dataset's characteristics. To assess the validity and reliability of the measurement model, Variance Inflation Factors (VIF) were employed with a threshold of less than 5, providing insights into multicollinearity among the independent variables. Additionally, path model analysis was conducted to investigate the relationships between the latent constructs.

3. Findings, Analysis, and Interpretation

The demographic composition presented in Table 1 shows the varied profiles of the participants, enhancing the generalizability and applicability of our findings. With a near-even split between male (48.90%) and female (51.10%) participants, our study ensured a balanced representation based on sex. The age distribution indicates a concentration of participants within the 21–30 age group (69.70%), and a significant representation of those aged 20 years or younger (26.10%). Regarding participants' education level, the majority hold undergraduate degrees (90.80), this robust representation underscores the alignment of our research focus with the intended participant group. The prevalence of undergraduates in our sample validates that our study is appropriately directed towards this specific cohort, providing a solid foundation for drawing meaningful conclusions and insights within the context of mHealth acceptance. In terms of career, majority of the participants are students (88.00%), while participants from enterprises, civil services, education, freelancing, and other professions collectively contribute to a diverse sample in terms of occupational background (11.00%). The income distribution aspect highlights the socioeconomic diversity of our participants, with a substantial majority earning 0–100,000 naira per month (92.60%). Lastly, participants' varied mobile phone usage experience, ranging from 1 to 3 years to more than 10 years, suggests a nuanced exploration of mHealth acceptance across participants with diverse levels of technological familiarity.

Table 1. Demographic information of the participants

Sex		
Male	139	48.90%
Female	145	51.10%
Age range (years)		
≤ 20	74	26.10%
21–30	198	69.70%
31–40	9	3.20%
41–50	2	0.70%
51–60	1	0.40%
Education level		
High school	15	5.30%
Undergraduate degree	258	90.80%
Master's degree	9	3.20%
Doctoral degree or higher	2	0.70%
Career		
Students	250	88.00%
Enterprises (state or foreign owned)	7	2.50%
Civil servants	2	0.70%
Educators	7	2.50%
Freelancers	2	0.70%
Others	16	5.60%
Monthly income (Naira)		
0–100,000	263	92.60%
101,000–200,000	12	4.20%
210,000–300,000	6	2.10%
301,000–400,000	1	0.40%
≥ 400,000	2	0.70%
Mobile phone usage experience (years)		
1–3	95	33.40%
4–7	80	28.20%
8–10	51	18.00%
> 10	58	20.40%
	284	100.00%

An important aspect of our research involved a thorough VIF analysis, further details of which are presented in Appendix C. Notably, the columns constituting section "B" (in the table presented in Appendix C) show results from analyses specifically conducted to guide the elimination of constructs deemed invalid. In section "A" of the table, we observe generally low VIF values, affirming the overall independence of our model's variables. However, items HC2 and HC3, with VIF values of 5.579 and 5.333, respectively, indicate a potential issue of multicollinearity. Subsequently, section "B" of the table was generated with a focus on refining our model. In section "B," the absence of HC2 and HC3 suggests their exclusion from further analysis, aligning with our intention to eliminate constructs that might introduce multicollinearity and compromise the validity of our findings. The overall pattern in section "B" continues to display consistently low VIF values, reinforcing the robustness of the refined model. This strategic VIF analysis (especially reported in section "B") serves as a crucial step in enhancing the reliability of our research results by ensuring the exclusion of constructs that could introduce redundancy or interdependence.

The assessment of the measurement model (Appendix D) involved evaluating the outer loadings, Cronbach's alpha, composite reliability (rho_a), and average variance extracted (AVE) for each construct. For Perceived Risk (PR), the outer loadings ranged from 0.796 to 0.897, indicating satisfactory convergent validity. The high Cronbach's alpha (0.917) and strong composite reliability measures (rho_a = 0.917) suggest robust internal consistency, with an AVE of 0.751, thus indicating good reliability. Facilitating Conditions (FC) exhibited outer loadings ranging from 0.843 to 0.893, a Cronbach's alpha of 0.844, and strong composite reliability (rho_a = 0.852), supported by an AVE of 0.761, indicating good reliability. Social Influence (SI) demonstrated strong reliability and convergent validity, with a Cronbach's alpha of 0.911, robust composite reliability (rho_a = 0.912), and an AVE of 0.849. Effort Expectancy (EE) displayed good convergent validity, with outer loadings ranging from 0.872 to 0.909, a Cronbach's alpha of 0.917, and strong composite reliability (rho_a = 0.918), supported by an AVE of 0.801. Performance Expectancy (PE) exhibited strong reliability and convergent validity, with outer loadings ranging from 0.883 to 0.925, a Cronbach's alpha of 0.893, and robust composite reliability (rho_a = 0.898), as confirmed by an AVE of 0.824. Trust (TR) demonstrated strong reliability and convergent validity, with a Cronbach's alpha of 0.928, robust composite reliability (rho_a = 0.929), and an AVE of 0.823. Health Consciousness (HC) displayed excellent internal consistency, with a Cronbach's alpha of 0.929 and convergent validity with outer loadings ranging from 0.901 to 0.914, strong composite reliability (rho_a = 0.93), and an AVE of 0.824. Behavioral Intention (BI) also demonstrated strong internal consistency with a Cronbach's alpha of 0.919 and convergent validity with outer loadings ranging from 0.917 to 0.943, robust composite reliability (rho_a = 0.92), and an AVE of 0.861.

Heterotrait-Monotrait Ratio (HTMT) analysis (Appendix E) was conducted to assess the discriminant validity among the latent constructs. The results demonstrated strong discriminant validity, with all HTMT values well below the widely accepted threshold of 0.85. Notably, Behavioral Intention (BI) to Effort Expectancy (EE) showed an HTMT value of 0.803, and BI to Facilitating Condition (FC) showed a value of 0.782, manifesting substantial separation. These values firmly establish the distinctiveness of these constructs, aligning with our expectations. Although Performance Expectancy (PE) to Effort Expectancy (EE) displayed a slightly elevated value of 0.942, Health Consciousness (HC) to Behavioral Intention (BI) displayed a value of 0.94, and Trust (TR) to Behavioral Intention (BI) showed a value of 0.932, indicating a potential shared variance among these constructs; yet, the values fall within the acceptable range when considering the holistic view of the model. The HTMT values for Social Influence (SI) to Facilitating Condition (FC) of 0.787, SI to Effort Expectancy (EE) of 0.808, and SI to Performance Expectancy (PE) of 0.839, all point to good discriminant validity. The lowest HTMT values reported between Perceived Risk (PR) and other constructs, such as Behavioral Intention (BI) at 0.431, Effort Expectancy (EE) at 0.418, and Performance Expectancy (PE) at 0.376, affirm strong discriminant validity. The value for Trust (TR) to Health Consciousness (HC) of 0.926, although high, does not exceed the threshold, suggesting sufficient discriminant validity. Our decision to use HTMT analysis, along with careful consideration of the absence of a universally agreed-upon threshold, strengthens the validity of our results and contributes to the ongoing discourse on the discriminant validity of latent constructs in SEM.

3.1 Results of Hypotheses Testing

Hypotheses concerning the variables that may predict the acceptance of mHealth technologies were tested by examining the relationships between Health Consciousness, Social Influence, Facilitating Conditions, Perceived Risk, Trust, Performance Expectancy, and Effort Expectancy, and their impact on Behavioral Intentions in the context of mHealth. The SEM diagram (Figure 3) explains the relationships between various constructs believed to influence the acceptance of mHealth technologies. The model includes both exogenous and endogenous variables. The exogenous variables are Health Consciousness (HC), Social Influence (SI), and Facilitating Conditions (FC). These are independent constructs hypothesized to influence the endogenous variables, which include Perceived Risk (PR), Trust (TR), Performance Expectancy (PE), Effort Expectancy (EE), and Behavioral Intentions (BI). The relationships between the variables are depicted by arrows pointing from the predictive constructs to the outcomes, with each arrow labeled with a beta coefficient indicating the strength and direction of the relationship. The R-squared values are shown in the circles next to the endogenous variables, representing the amount of variance in the outcomes explained by the model.

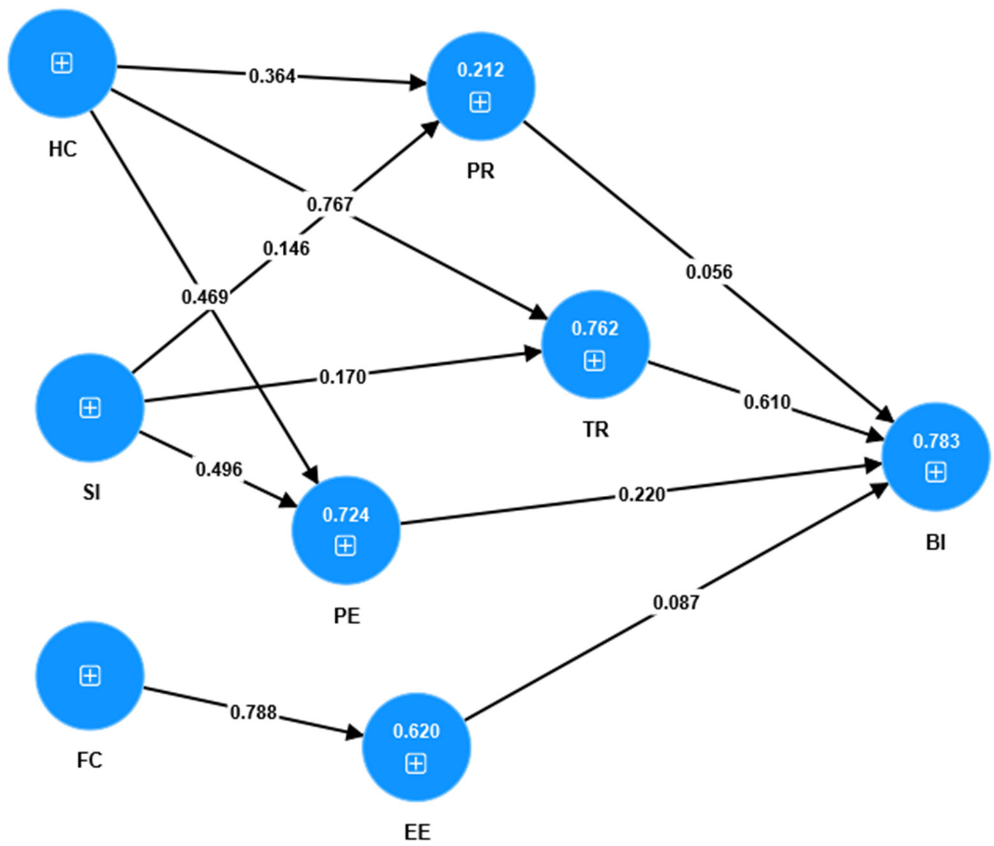

Figure 3. Structural model

H1 was predicated on the idea that concerns about privacy, data security, or potential errors might deter users' intentions to use mHealth services. However, a beta coefficient of 0.056 with a p-value of 0.091 did not support this hypothesis, suggesting that perceived risk does not significantly deter users' intentions to use mHealth services.

H2 suggests that trust in the reliability, security, and credibility of mHealth services encourages users to engage with such technologies. The results support this hypothesis, revealing a strong positive relationship between trust and behavioral intentions to use mHealth technologies. Users who trust mHealth services are more likely to use them, as suggested by a high beta coefficient of 0.61 and a p-value of 0.

H3 suggests that mHealth would be beneficial and improve health outcomes, and is expected to impact the intention to use these services positively. This hypothesis was supported, as indicated by a beta coefficient of 0.22 and a p-value of 0.001, suggesting that performance expectancy is a significant predictor of users' behavioral intentions to use mHealth technologies.

H4 posits that if mHealth services are perceived as user-friendly and easy to use, this would increase the likelihood of their adoption by users. Contrary to this hypothesis, the beta coefficient of 0.087, with a p-value of 0.204, suggests that effort expectancy may not significantly influence behavioral intentions to use mHealth technologies.

H5a suggests that individuals who are more conscious of their health would perceive mHealth to be less risky. This hypothesis was supported, as reflected by a beta coefficient of 0.364 and a p-value of 0, indicating that higher health consciousness is associated with lower perceived risk in the context of mHealth.

H5b suggests that individuals who prioritize their health are more likely to trust mHealth applications, potentially because of a greater propensity to seek and use health-related technologies. This hypothesis was supported by the results, with a beta coefficient of 0.767 and a p-value of 0, suggesting a strong positive relationship between health consciousness and trust in mHealth technologies.

H5c posits that those with higher levels of health consciousness would perceive mHealth as more important and develop an interest in mHealth to support their health goals. This was supported by a beta coefficient of 0.469 and a p-value of 0, indicating that health-conscious individuals find mHealth services to be more beneficial.

H6a proposes that the influence of peers and social networks could alleviate concerns about mHealth risks as users might rely on the experiences and recommendations of others. The beta coefficient of 0.146, with a p-value of 0.048, supports this hypothesis, suggesting that social influence reduces the perceived risks associated with mHealth technologies.

H6b suggests that endorsements from social circles would enhance trust in mHealth services, positing that social validation enhances trust. A beta coefficient of 0.170 and a p-value of 0 support this hypothesis, indicating that social influence positively affects trust in mHealth technologies.

H6c posits that social influence could lead to a higher perception of mHealth benefits, as users often take cues from others' successful use of mHealth technologies. A beta coefficient of 0.496 and a p-value of 0 support the idea that social influence enhances the perceived usefulness of mHealth technologies.

H7 suggests that the presence of supportive conditions makes it easier for individuals to use mHealth technologies, thereby positively affecting their intention to engage with such services. A beta coefficient of 0.788 and a p-value of 0 support this hypothesis.

Table 2. Hypotheses testing results

Hypothesis	Beta coefficient	Standard deviation	T statistics	P values	Result
PR -> BI	0.056	0.033	1.691	0.091	Not supported
TR -> BI	0.610	0.062	9.914	0	Supported
PE -> BI	0.220	0.067	3.263	0.001	Supported
EE -> BI	0.087	0.068	1.27	0.204	Not supported
HC -> PR	0.364	0.068	5.34	0	Supported
HC -> TR	0.767	0.032	23.702	0	Supported
HC -> PE	0.469	0.046	10.239	0	Supported
SI -> PR	0.146	0.074	1.978	0.048	Supported
SI -> TR	0.170	0.036	4.743	0	Supported
SI -> PE	0.496	0.045	10.984	0	Supported
FC -> EE	0.788	0.024	33.169	0	Supported

4. Discussion

The scope of healthcare delivery is increasingly being shaped by the evolution and integration of mHealth technologies (Kageyama et al., 2022). Studies—spanning from basic to applied research—indicate that technological advancements related to mHealth tools and their impact on healthcare provision, incorporating various mHealth applications and devices such as wearable sensors, mobile apps, and remote monitoring systems, have greatly contributed to the improvement of healthcare delivery and patient outcomes (Hashiguchi et al., 2021; Niwa et al., 2022). Understanding the social value through social enterprises (Kurata et al., 2023) will also foster the adoption rates of these technologies across different populations, ensuring equitable access and maximizing their potential benefits. Exponential growth in mHealth research indicates a shift from health policy to the development and social application of mHealth technologies, reflecting a changing focus in the mHealth field (Cao et al., 2021), thus increasing its relevance and role in healthcare delivery within developing countries. The current study involved a comprehensive analysis based on the UTAUT model and the dimensions and constructs proposed by Cao et al. (2022; explained above) to investigate the acceptance and use of mHealth technologies in developing nations. Our findings revealed a significant positive influence of Trust (with a beta coefficient of 0.610 and a p-value of 0) and Performance Expectancy (with a beta coefficient of 0.220 and a p-value of 0.001) on the behavioral intentions to use mHealth technologies in the future among the young population in Nigeria. This indicates that both trust in mHealth services and the perceived benefits regarding performance are central to users' decision-making process. These results underscore the necessity of initiatives aimed at building trust in mHealth services and demonstrate their effectiveness in ensuring future acceptance. Contrary to our initial hypotheses, Effort Expectancy (EE) and Perceived Risk (PR) were not as influential as anticipated, with Effort Expectancy showing a beta coefficient of 0.087 and a p-value of 0.204 and Perceived Risk presenting a beta coefficient of 0.056 and a p-value of 0.091. This suggests that the ease of use of mHealth applications and the potential risks associated with them may not be significant determinants of their adoption among young Nigerians. This suggests that while usability and risk considerations are relevant, they do not serve as the primary drivers in the adoption of mHealth services within this demographic. Meanwhile, regarding Personal Characteristics (PC), Health Consciousness (HC) demonstrated a significant positive effect on both Perceived Usefulness (PE) (with a beta coefficient of 0.469 and a p-value of 0) and Trust (TR) (with a beta coefficient of 0.767 and a p-value of 0). This indicates that individuals who are more health conscious are likely to perceive mHealth as both useful and trustworthy. This finding suggests that mHealth initiatives should focus on raising health awareness to enhance positive perceptions and credibility of their services. Moreover, the role of Social Influence (SI) was found to be significant, positively affecting Perceived Usefulness (PE) (with a beta coefficient of 0.496 and a p-value of 0) and inversely affecting Perceived Risk (PR) (with a beta coefficient of 0.146 and a p-value of 0.048). This reflects the importance of social networks in shaping perceptions of mHealth in Nigeria, where community and peer opinions play a crucial role in reducing apprehensions and reinforcing the perceived advantages of mHealth services. Lastly, the Conditions of Use dimension, represented by Facilitating Conditions (FC), had a significant positive effect on Effort Expectancy (EE), as evidenced by a beta coefficient of 0.788 and a p-value of 0. This finding emphasizes the importance of providing accessible and user-friendly mHealth platforms with adequate support to facilitate their adoption among young individuals. The implications of these findings for developing countries are substantial. The pivotal roles of trust and performance expectancy indicate that mHealth initiatives should focus on developing credible and effective solutions. Additionally, the influence of health consciousness and social dynamics on the acceptance of mHealth services highlights the need for targeted strategies to enhance the acceptance of mHealth. However, the lesser importance of effort expectancy and perceived risk suggests that other factors should be prioritized over mere usability and risk mitigation for the successful adoption of mHealth services in these regions.

5. Conclusion

Our study on the social acceptance of mHealth among the young population in Nigeria highlights the systematic nature of the future integration of mHealth into the healthcare delivery system. The empirical findings reveal that factors such as Trust (TR), Performance Expectancy (PE), Health Consciousness (HC), and Social Influence (SI) play crucial roles in shaping behavioral intentions to use mHealth technologies. Trust and perceived effectiveness of mHealth technologies have been identified as primary drivers of their adoption among the young population, emphasizing the need for dependable and effective mHealth solutions. Health Consciousness emerges as a significant personal characteristic that influences perceptions of the usefulness and trustworthiness of mHealth technologies, thus highlighting the potential of mHealth initiatives to enhance health awareness. Social Influence further underscores the importance of community and peer opinions in shaping mHealth perceptions, reducing apprehension, and reinforcing perceived advantages. However, this study identified several potential barriers to the widespread acceptance and effectiveness of mHealth technologies in Nigeria. These include the digital divide, sociocultural factors, policy and regulatory gaps, and concerns regarding data privacy and security. Addressing these barriers requires a systematic approach involving governments, healthcare providers, technology developers, and communities (rural and urban). The insights obtained from our investigation not only provide a deeper understanding of the intricate dynamics surrounding mHealth acceptance in Nigeria but also emphasize the wider relevance of these findings in similar developing environments laying the groundwork for developing strategies to enhance the effectiveness and accessibility of mHealth solutions in different regions facing similar healthcare delivery challenges. The current health situation in Nigeria, characterized by inadequate infrastructure, healthcare personnel shortages, and a high disease burden, presents both challenges and opportunities for mHealth. Although mHealth has the potential to bridge healthcare gaps, enhance disease management, and improve health education, its success depends on effectively overcoming these barriers. Overall, this study contributes to a deeper understanding of the factors influencing the social acceptance of mHealth in developing countries such as Nigeria. It provides insights for tailoring mHealth initiatives to meet the specific needs and preferences of young individuals, thereby enhancing the accessibility, affordability, and effectiveness of healthcare services in these regions.

5.1 Recommendations

Developing targeted mHealth programs for prevalent health issues in Nigeria is crucial. Collaborative initiatives with telecomunication companies to improve network infrastructure in rural and expanding urban areas will ensure wider mHealth service accessibility, thus increasing its acceptance rate. The establishment and enforcement of government policies to support and regulate mHealth services are vital for maintaining their quality and reliability.

Training healthcare professionals to use mHealth tools will be increasingly important for improving patient engagement and care management in young populations. Public awareness campaigns among the young population are recommended to continuously educate the expanding population about the benefits and usage of mHealth services, building trust and acceptance. These are possible measures that can be taken to fully exploit the potential of mHealth to revolutionize healthcare delivery in Nigeria while keeping pace with its young population.

5.2 Limitations and Future Research

Although informative, the current study has limitations that should be addressed in future studies. First, the sample was limited to undergraduate students, suggesting a potential bias that may restrict the applicability of the findings to other demographics or populations. Additionally, as a cross-sectional study, the results only reflect attitudes and behaviors at a specific time point without considering potential changes over time. Furthermore, there might be additional variables that were not considered that could affect mHealth use. Future studies should aim for more diverse samples, consider longitudinal designs to observe changes over time, and include a wider range of variables to comprehensively understand the factors influencing mHealth use. Recognizing the rapid evolution of mHealth technologies and considering the influence of cultural factors is extremely important. These factors can greatly affect the relevance of our findings. Future research can also focus on key areas that can enhance the effectiveness of mHealth, like user interface design. Addressing these areas will not only improve mHealth services in Nigeria but also provide a blueprint for their adaptation and successful implementation in other developing countries facing comparable healthcare challenges.

Acknowledgments

We are grateful to the funding source that supported this study. We would like to express our gratitude to our colleagues who have contributed significantly to the research in different aspects. A special mention should be made to the collaborative efforts among the authors. Finally, we would like to express our sincere gratitude for the valuable assistance provided during the preparation of the manuscript.

Funding

None.

Informed Consent

Obtained.

Provenance and Peer Review

Not commissioned; externally double-blind peer reviewed.

Data Availability Statement

The data that support the findings of this study are available on request.

Competing Interests Statement

The authors declare that there are no competing or potential conflicts of interest.

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Appendix A

Hypotheses Based on Constructs from Cao et al.'s (2022) Study

Hypothesis	Description
H1	Perceived risk negatively affects behavioral intentions regarding mHealth technologies.
H2	Trust positively influences behavioral intentions regarding mHealth technologies.
H3	Performance expectancy has a positive effect on behavioral intentions regarding mHealth technologies.
H4	Effort expectancy has a positive effect on behavioral intentions regarding mHealth technologies.
H5a	Health consciousness has a negative effect on the perceived risk of mHealth technologies.
H5b	Health consciousness has a positive effect on trust related to mHealth technologies.
H5c	Health consciousness has a positive effect on the perceived usefulness of mHealth technologies.
H6a	Social influence has a negative effect on the perceived risk of using mHealth technologies.
H6b	Social influence has a positive effect on trust related to mHealth technologies.
H6c	Social influence has a positive effect on the perceived usefulness of mHealth technologies.
H7	Facilitating conditions have a positive effect on effort expectancy regarding mHealth technologies.

Appendix B

Survey Items Based on Cao et al.'s (2022) Study

Construct	Items description	
Performance Expectancy (PE)	PE1	I find mHealth services useful in my daily life.
	PE2	Using mHealth services helps me accomplish things more quickly.
	PE3	Using mHealth services increases my productivity.
Effort Expectancy (EE)	EE1	Learning how to use mHealth services is easy for me.
	EE2	My interaction with mHealth services is clear and understandable.
	EE3	I find mHealth services easy to use.
	EE4	It is easy for me to become skillful at using mHealth services.
Social Influence (SI)	SI1	People who are important to me think that I should use mHealth services.
	SI2	People who influence my behavior think that I should use mHealth services.
	SI3	People whose opinions I value prefer that I use mHealth services.
Facilitating Conditions (FC)	FC1	I have the resources necessary to use mHealth services.
	FC2	I have the knowledge necessary to use mHealth services.
	FC3	mHealth is compatible with other technologies I use.
Perceived Risk (PR)	PR1	I am afraid that mHealth providers cannot guarantee the confidentiality of user information.
	PR2	I am worried that my personal privacy information will be used for other purposes if I use mHealth services.
	PR3	I am worried that when using mHealth services, my personal information will be abused by cyber criminals.
	PR4	I am worried that my personal health-related information is not protected by law when using mHealth services.
	PR5	I am afraid that the rights and interests of users cannot be ensured because of the lack of specific law enforcement on mHealth services.
Trust (TR)	TR1	I have trust in academic researchers working on mHealth service projects.
	TR2	I have trust that mHealth services provide great value to the society.
	TR3	I have trust that the government will improve relevant regulations on mHealth services.
	TR4	I have trust that mHealth providers will improve user privacy management.

Health Consciousness (HC)	HC1	I reflect about my health a lot.
	HC2	I am very self-conscious about my health.
	HC3	I am generally attentive to my inner feelings about my health.
	HC4	I am constantly examining my health conditions.
	HC5	I think that I take health matters into account a lot in my life.
	HC6	I think it is important to know well how to eat healthily.
Behavioral Intention (BI)	BI1	I intend to use mHealth services in the future.
	BI2	I will always try to use mHealth services in my daily life.
	BI3	I plan to use mHealth services frequently.

Appendix C

Variance Inflation Factor Results

	A					B				
Items	Path Coe	Stand. Dev.	T statistics	P values	VIF	Path Coe.	Stand. Dev.	T statistics	P values	VIF
BI1	0.915	0.014	64.949	0	3.021	0.915	0.014	65.545	0	3.021
BI2	0.944	0.008	123.186	0	3.983	0.943	0.008	121.534	0	3.983
BI3	0.925	0.013	73.838	0	3.327	0.925	0.012	74.022	0	3.327
EE1	0.909	0.012	75.223	0	3.269	0.909	0.012	75.262	0	3.269
EE2	0.902	0.015	60.939	0	3.066	0.901	0.015	60.546	0	3.066
EE3	0.902	0.014	62.874	0	3.058	0.902	0.014	63.024	0	3.058
EE4	0.866	0.02	42.882	0	2.521	0.867	0.02	43.174	0	2.521
FC1	0.832	0.024	35.408	0	1.903	0.834	0.023	35.849	0	1.903
FC2	0.899	0.015	59.706	0	2.24	0.898	0.015	58.098	0	2.24
FC3	0.884	0.015	60.823	0	1.992	0.883	0.014	60.917	0	1.992
HC1	0.908	0.015	58.955	0	4.116	0.91	0.014	63.591	0	3.426
HC2	0.933	0.01	96.341	0	5.579					
HC3	0.932	0.011	88.367	0	5.333					
HC4	0.902	0.014	65.126	0	4.058	0.905	0.013	69.665	0	3.329
HC5	0.881	0.023	38.741	0	3.365	0.9	0.019	47.092	0	3.204
HC6	0.908	0.015	60.638	0	4.176	0.915	0.012	76.237	0	3.475
PE1	0.916	0.012	76.504	0	2.794	0.915	0.012	76.409	0	2.794
PE2	0.925	0.012	80.28	0	3.109	0.925	0.012	79.839	0	3.109
PE3	0.882	0.02	44.87	0	2.363	0.883	0.019	45.404	0	2.363
PR1	0.817	0.023	35.631	0	2.029	0.817	0.023	35.723	0	2.029
PR2	0.903	0.012	75.494	0	3.788	0.903	0.012	75.816	0	3.788
PR3	0.889	0.016	55.549	0	3.301	0.889	0.016	55.376	0	3.301
PR4	0.878	0.023	37.56	0	4.129	0.878	0.023	38.011	0	4.129
PR5	0.838	0.024	35.391	0	2.956	0.837	0.024	35.277	0	2.956
PV1	0.875	0.021	42.107	0	2.323	0.874	0.021	41.748	0	2.323
PV2	0.934	0.009	105.018	0	3.465	0.934	0.009	103.435	0	3.465
PV3	0.908	0.014	63.455	0	2.726	0.909	0.014	65.447	0	2.726
SI1	0.919	0.011	81.56	0	2.992	0.919	0.011	80.994	0	2.992

SI2	0.928	0.012	75.864	0	3.375	0.928	0.012	76.612	0	3.375
SI3	0.918	0.011	80.085	0	2.955	0.917	0.012	78.882	0	2.955
TR1	0.89	0.019	46.658	0	2.933	0.89	0.019	46.796	0	2.933
TR2	0.931	0.009	102.296	0	4.153	0.931	0.009	102.797	0	4.153
TR3	0.908	0.015	62.17	0	3.366	0.907	0.015	61.989	0	3.366
TR4	0.901	0.018	49.678	0	3.281	0.9	0.018	48.752	0	3.281

Appendix D

Summary of Construct Validity Results

Items	Outer loadings	Cronbach's alpha	Composite reliability (rho_A)	Average variance (AVE)
EE	0.917	0.918	0.942	0.801
FC	0.844	0.852	0.905	0.761
HC	0.929	0.93	0.949	0.824
PE	0.893	0.898	0.934	0.824
PR	0.917	0.917	0.938	0.751
SI	0.911	0.912	0.944	0.849
TR	0.928	0.929	0.949	0.823
BI	0.919	0.92	0.949	0.861

Appendix E

Discriminant Validity Results

. Before

	BI	EE	FC	HC	PE	PR	TR
BI							
EE	0.803						
FC	0.782	0.89					
HC	0.93	0.753	0.697				
PE	0.853	0.942	0.866	0.806			
PR	0.431	0.418	0.438	0.469	0.376		
SI	0.701	0.808	0.787	0.601	0.839	0.378	
TR	0.932	0.786	0.76	0.915	0.83	0.413	

After

	BI	EE	FC	HC	PE	PR	SI	TR
BI								
EE	0.803							
FC	0.782	0.89						
HC	0.94	0.759	0.704					
PE	0.853	0.942	0.866	0.813				
PR	0.431	0.418	0.438	0.479	0.376			
SI	0.701	0.808	0.787	0.604	0.839	0.378		
TR	0.932	0.786	0.76	0.926	0.83	0.413	0.648	