REVOLUTIONIZING HEALTHCARE: THE SURGE OF mHEALTH ADOPTION IN THE DIGITAL ERA

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ABSTRACT

The surge in smartphone and tablet use has rapidly boosted mHealth adoption, providing enhanced computing and communication for improved patient health and streamlined communication with healthcare providers. Positioned as a cost-effective alternative for healthcare delivery, mHealth is anticipated to transform the industry, making it a crucial tool for addressing health concerns. This study focuses on understanding factors influencing the perception and usage patterns of mHealth apps among the tech-savvy younger population. The research model incorporates variables derived from the well-accepted UTAUT2 (Unified Theory of Acceptance and Use of Technology) and TAM (Technology Acceptance Model), alongside considerations of privacy, security, and trust. Information was gathered from a representative set of 250 individuals utilizing mobile health (mHealth) applications in India, and the analysis will be conducted using Structural Equation Modeling-Partial Least Squares (SEM-PLS). The study empirically explores the soundness of extensions based on the Expectation Confirmation Theory (ECT) concerning users' ongoing behavior regarding mHealth apps. Findings indicate that factors can positively impact perceived usefulness, influencing the continuous intention to use mHealth apps.

Keywords: m-health apps, Privacy, Security, Trust, Continuous Intention, Expectation Confirmation Theory (ECT)

INTRODUCTION

Health Information Technologies (HITs) comprise a diverse range of products and services, including assistive technology, sensors (Jaber *et al*., 2022; Sun *et al*., 2022), cloud-based services (Ofori *et al*., 2021), electronic health records (EHRs) (Alsyouf *et al*., 2022; Alsyouf & Abdullah, 2018), mobile health technologies (AL-Mugheed *et al*., 2022), medical devices, telemonitoring tools, and telehealth (Ardielli, 2021). These technologies facilitate the collection, sharing, and utilization of health information among individuals, healthcare professionals, and community-based healthcare institutions (Alsyouf *et al*., 2022; Alsyouf & Abdullah, 2018; Jaber *et al*., 2022). With global healthcare systems grappling with rising costs and significant disease burdens (Keehan *et al*., 2017), digital health innovations (Keehan *et al*., 2017), such as mobile health apps (mHealth), are increasingly utilized to address these challenges (Simons *et al*., 2015; Whitehead & Seaton, 2016).

MHealth apps have the potential to enhance patient autonomy, health literacy, and quality of life. They support better symptom management (Whitehead & Seaton, 2016), increased adherence to chronic illness management (Hamine *et al*., 2015), and a reduction in the prevalence of chronic diseases (Fan & Zhao, 2022). However, acquiring patient medical records outside the hosting authority's jurisdiction can be difficult, particularly considering the growing trend of global healthcare seeking. Information and communication technology (ICT) emerges as a viable solution for corporate-to-corporate transfers of personal medical data (Esmaeilzadeh & Sambasivan, 2016).

With the challenges posed by COVID-19 (Mira *et al*., 2021; Mitra & Basu, 2020; Roy *et al*., 2021), ensuring access to healthcare becomes crucial (Houlding *et al*., 2021), especially during lockdown situations or while managing COVID-19 cases. MHealth apps play a pivotal role in improving accessibility, addressing issues within the global healthcare system, and providing essential care while minimizing in-person interactions (Lin & Lou, 2021; Melin *et al*., 2020; Nguyen *et al*., 2022; Nicholas *et al*., 2021; Singh *et al*., 2020).

MHealth, a subset of eHealth, leverages digital communication and electronic technologies to enhance healthcare delivery (Alenoghena *et al*., 2022). Designed for mobile devices, mHealth is more accessible than traditional eHealth (Melin *et al*., 2020), offering services like medication reminders, fitness tracking, mental health support, symptom tracking, and access to health-related data (Chen & Xu, 2022; Ni *et al*., 2022). The WHO (World Health Organization) defines mHealth as using mobile devices for real-time healthcare data collection (Quiñonez *et al*., 2016; WHO Global Observatory for eHealth., 2011a), patient monitoring, diagnosis, and treatment, understanding the potential advantages it provides for both patients and healthcare professionals (Almotiri *et al*., 2016; Singh *et al*., 2020; WHO Global Observatory for eHealth., 2011b).

MHealth apps utilize location data and proximity alerts to notify users of possible exposure to chronic diseases (Artanian *et al*., 2020; El-Sherif *et al*., 2022), enabling self-isolation, testing, and breaking the transmission chain. They also improve medication adherence, permit data sharing, facilitate remote consultations, and educate patients about diseases (Ni *et al*., 2022; Sleurs *et al*., 2019; Smith *et al*., 2015; Yang *et al*., 2021).

However, ethical concerns related to user behavior in contact tracking apps (Ahmed *et al*., 2020; Altmann *et al*., 2020), along with a lack of knowledge regarding user interaction with mobile health apps pertaining to community care and health maintenance (Alam *et al*., 2020; Banskota *et al*., 2020), warrant further exploration. This study aims to empirically investigate the relationships between security, trust, privacy concerns, and the long-term intention to use mHealth apps. The emotional components of these factors are analyzed to understand their influence on the habit of using mobile Health apps for health maintenance.

There are five sections to the study. Section 2 begins with a review of the literature; Section 3 describes the research methodology; and Section 4 presents the findings. Section 5 presents the conclusion, along with a consideration of its limitations and suggestions for future lines of inquiry.

LITERATURE REVIEW

Mobile health (mHealth) emerges from telehealth, utilizing information technologies for remote healthcare services (Dobson *et al*., 2017). The term "mHealth" globally signifies the integration of mobile technologies in healthcare services (Klasnja & Pratt, 2012; Martínez-Pérez *et al*., 2013). Mobile and wireless technologies can enhance health system efficiency and outcomes (Rose *et al*., 2017). Key benefits of mHealth apps include self-health tracking, chronic condition management, and cost reduction, especially in remote areas of developing nations (Khalemsky & Schwartz, 2017; Valle *et al*., 2020).

Privacy is vital when accessing health-related information through mobile apps (Luxton *et al*., 2011). The privacy calculus model (Xu *et al*., 2011) suggests that users weigh risks and benefits before sharing information. Consequently, the hypothesis posited is:

H_1: Privacy Concern significantly associated with the usefulness of m-health apps.

Security issues have a substantial impact on transactions conducted online (Alsaggaf, 2017). Security, defending systems against threats, theft, and unauthorized access, applies to electronic health records and online transactions. Thus, the hypothesis is:

H_2: Security significantly associated with the usefulness of m-health apps.

Trust is crucial in eHealth/mHealth acceptance, influencing adoption behavior (Wu *et al*., 2011). Trust in data analysis and monitoring is particularly significant. Hence, the hypothesis is:

H_3: Trust significantly associated with the usefulness of m-health apps.

Users express a need for mHealth apps when faced with obstacles preventing regular doctor visits (Lemke *et al*., 2011; Miele *et al*., 2020; Tebeje & Klein, 2021). Expectation Confirmation Theory (ECT) and perceived usefulness, validated in explaining information system behavior, are pertinent (Bhattacherjee, 2001; Davis, 1989). The continuity intention (CI) denotes a user's intention to keep using mHealth apps, emphasizing user commitment. Previous studies show perceived usefulness positively impacts CI (Cho, 2016). Therefore, the hypothesis is:

H_4: Perceived Usefulness significantly associated with the continuance intention to use m-health apps.

In summary, this study explores the relationships between privacy concern, security, trust, perceived usefulness, and the intention to continue using mHealth apps.

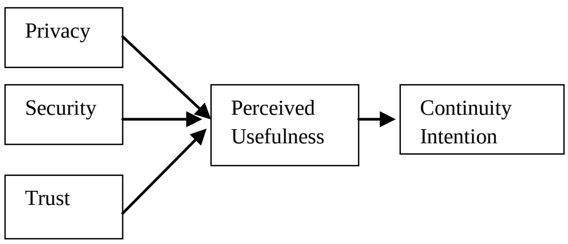

Figure 1: Conceptual Framework for the Study

RESEARCH METHODOLOGY

This study aims to investigate the interconnections among various factors that influence the adoption of mHealth. Through the addition of various components, it alters the conventional Technology Acceptance Model (TAM). The context of mHealth adoption in India, specifically Delhi NCR/ Gurugram, has been examined. To bridge gaps in existing research, this study seeks to conduct a primary survey using 5-point Likert Scale.

Before conducting the main survey, it was crucial to identify participants based on their use of Android smartphones, internet accessibility, and age (18 years or older). The decision to use this age criterion was to maintain stable responses, particularly since individuals under 18 often encounter limitations on phone access. Due to the lack of a clearly defined population frame, judgmental sampling was utilized to optimize the efficient use of resources. The research centered around mHealth app usage in Indian regions like Delhi-NCR and Gurugram, selecting widely used apps (Practo, mfine, DocsApp, etc.) for reliability and validity. A screening question ("Have you ever used any mHealth apps applications?") ensured participants possessed hands-on experience with mHealth apps. Invitations were extended to Delhi NCR and Gurugram residents, with data collection occurring continuously three months (October-November-December) in 2023, resulting in 209 valid samples after excluding 41 participants lacking mHealth app experience.

RESULTS

Data Analysis

Using the methodology described by (Sarstedt *et al*., 2022), this study used the (Partial Least Squares Structural Equation Modeling) PLS-SEM) software from Smart PLS4. PLS-SEM's strengths lie in its flexibility with small sample sizes and its ability to handle complex models (Hair, 2014). According to Anderson *et al*. (1988), the structural model was estimated after the measurement model had been validated.

Measurement Model

Initially, this study ensured the internal consistency of measures for each construct. As depicted in Table 1, both Cronbach's alpha and composite reliability values surpassed the recommended threshold of 0.7, affirming the reliability of all constructs. Subsequently, convergent validity was scrutinized through examination of factor loadings and average variance extracted (AVE). Table 1 illustrates factor loadings exceeding 0.7 and AVE values surpassing 0.5, in accordance with the guidelines by Hair *et al*. (2017), confirming convergent validity.

Discriminant validity was evaluated using the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) criterion. The Fornell–Larcker criterion necessitates the square root of the AVE for each construct to exceed its correlations with other constructs, while the HTMT criterion mandates a ratio lower than 0.9 (Fornell & Larcker, 1981; Henseler *et al*., 2015). As outlined in Table 2, this study encountered no discriminant validity issues. Model fit was assessed using the standardized root mean square residual (SRMR). The SRMR value for the research model, recorded at 0.058, signifies a well-fitting model, aligning with standards set by Henseler *et al*. (2016).

Table 1: Measurement Model

Constructs	Items	Mean	Loadings	Cronbach's alpha	Composite Reliability	AVE
Continue Intention	CI1	3.258	0.889	0.937	0.938	0.888
	CI2	3.287	0.878			
	CI3	3.411	0.817			
Perceived Usefulness	PU1	3.23	0.852	0.938	0.938	0.890
	PU2	3.292	0.807			
	PU3	3.392	0.885			
Privacy	Privacy1	3.344	0.834	0.912	0.913	0.850
	Privacy2	3.306	0.803			
	Privacy3	3.349	0.852			
Security	Security1	3.148	0.907	0.896	0.897	0.828
	Security2	3.153	0.917			
	Security3	3.225	0.972			
Trust	Trust1	3.273	0.945	0.946	0.950	0.902
	Trust2	3.421	0.934			
	Trust3	3.325	0.920			

Source: Author's own research

Table 2: Discriminant Validity

	1	2	3	4	5
Fornell-Larcker Criterion					
Continue Intention	0.943				
Perceived Usefulness	0.854	0.943			
Privacy	0.682	0.678	0.922		
Security	0.756	0.739	0.772	0.910	
Trust	0.854	0.864	0.717	0.811	0.950
Values along the diagonal (italic) denote the square root of the Average Variance Extracted (AVE), whereas the correlations are depicted on the off-diagonal elements.					
HTMT Criterion					
Continue Intention					
Perceived Usefulness	0.854				
Privacy	0.737	0.733			
Security	0.825	0.806	0.853		
Trust	0.792	0.703	0.772	0.881	

Source: Author's own research

Structural Model

A bootstrapping procedure involving 5,000 re-samples was executed to evaluate the significance of path coefficients. The outcomes of the path testing for the model are presented in Table 3. Privacy and security factors (H_1, H_2) exhibited a significant impact on the perceived usefulness of users, while trust (H_3) directly influenced perceived usefulness. Additionally, the effect of users' perceived usefulness (H_4) significantly influenced their continuance intention in the model. In summary, all hypotheses (H_1, H_2, H_3, H_4) garnered full support in this model analysis.

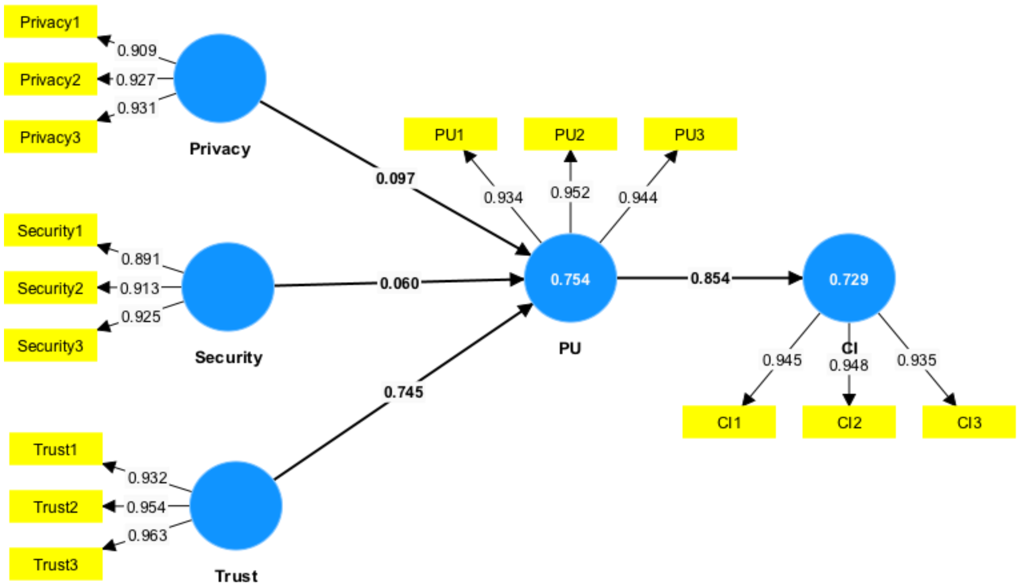

Figure 2: Result of Structural Model

To assess the explanatory power of the research model, we reported R^2, Q^2, and Q^2 predict, as illustrated in Figure 2. The Q^2 value, derived through a blinding folding procedure, should surpass zero, indicating the model's predictive relevance (Geisser, 1974; Stone, 1973). Furthermore, a Q^2 predict value greater than zero suggests that employing the PLS model provides greater predictive power, with smaller prediction errors, compared to using the average value of all observations (Hair *et al*., 2017).

Table 3: Results of Path Testing

Hypothesis/Path	Path coefficient	Decision
H1 Privacy>PU	0.097	Supported
H2 Security>PU	0.060	Supported
H3 Trust>PU	0.745	Supported
H4 PU>CI	0.854	Supported

Source: Author's own research

CONCLUSION

In the era of healthcare digital transformation, mHealth emerges as an innovative technology within the contemporary technological landscape. A committed research effort has been initiated to uncover the fundamental factors that drive the adoption of mHealth apps in India. Recognizing the relatively lower adoption rates among the tech-savvy younger generation, a recent realization has underscored the importance of comprehending and scrutinizing the key determinants of mHealth app adoption.

While governments throughout the world are using technology to effectively combat the COVID-19 pandemic, this study investigates India's persistent intention to use mHealth apps, the country with the highest population density. The research delves into the intricate connections among privacy, security, and trust, examining how these elements contribute to users' perceptions of sustained utility in mHealth apps and their intention to use them.

The suggested relationships are tested and validated using SEM (structural equation modeling). To achieve broad acceptance of mHealth app services, a unified framework needs to be developed and implemented by healthcare providers of all stripes. It is essential to incorporate mHealth app development projects into national healthcare programs, giving top priority to their compatibility with the current healthcare system. Public-private partnerships involving the government, community health workers, and cooperation between private and public hospitals are essential for achieving successful implementation.

Concerns about security and privacy are discussed in the study as possible roadblocks to technology adoption. The study highlights the beneficial impact of trust on perceived usefulness (H_3) in the Indian context and validates hypotheses H_1 and H_2 as significant. It has been demonstrated that users' confidence in the features and advantages of mHealth services is positively impacted by trust.

One important finding is that the intention to continue using mHealth apps is directly influenced by their perceived usefulness, which may be related to government mandates during the COVID-19 pandemic. To win over the public, future initiatives should concentrate on improving online medical features. The study identifies a robust correlation between adoption factors and the intention to persist in using the system. This aligns with prior research emphasizing the significance of user adoption in promoting the utilization of information systems.

The study does acknowledge its limitations, though. First off, results should be interpreted cautiously because data collection is limited to a single country. Second, while focusing on general mHealth apps, the study ignores specific variations. Thirdly, the sample is confined to urban areas, implying that future studies should encompass subjects from diverse backgrounds.

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