RESEARCH PAPER

Mobile health and its predictors of adoption among Healthcare Professionals in Developing Nations : A UTAUT Model Analysis

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ABSTRACT
Mobile health (mHealth) technology has transformed healthcare by enhancing disease management, diagnosis, outbreak tracking, and the delivery of medical advice. However, its adoption in developing countries remains limited. Using UTAUT, we investigated the factors influencing the behavioral intention to adopt mHealth, assessed its level of adoption in the Delhi NCR region, and examined the influence of demographics. Healthcare professionals (HCPs) in the Delhi NCR participated in the study. Data were collected from 384 respondents via Google Forms, WhatsApp, email, and in-person visits. "Partial Least Squares Structural Equation Modelling (PLS-SEM)" with "SMART PLS 4" assessed the measurement model and tested hypotheses. A mean score of 4.048 on a 5-point Likert scale (1="Strongly Disagree," 5=" Strongly Agree") indicates a high level of mHealth adoption among healthcare professionals. The model accounted for 58.8% of the variation in the intention to use mHealth applications. Social Influence exerted the most significant positive impact on the intention to adopt mHealth (β= 0.403, p = 0.005). Performance Expectancy also significantly affected adoption (β= 0.282, p = 0.002). An evident positive correlation was found between the intention to act and the actual usage behavior (β = 0.341, p = 0.000). The influence of "Facilitating Conditions" (β = 0.213, p = 0.055) and "Effort Expectancy"(β = 0.145, p = 0.270) was not found to be statistically significant . The effect of moderators on the intention to use mHealth was insignificant. The results will help governments promote mHealth adoption to improve health promotion and reduce inequities.

Keywords: mHealth adoption, Healthcare professionals, Moderators, Predictors, UTAUT Model
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INTRODUCTION

The WHO defines mHealth as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices." According to the Digital 2025 Global Statshot Report by DataReportal, 5.65 billion individuals are internet users (68.7% of the world population), while 5.41 billion use social media (65.7%). Mobile phones have become prevalent in healthcare[1]. mHealth apps provide individualised services at reasonable prices and can reach underserved populations due to their geographical reach[2]. Medication apps serve as reminders[3] and assist in maintaining records, clinical decision-making, patient monitoring, time management, communication, and medical education[4]. Studies show health behavior interventions successfully enhance lifestyle behaviors like diabetes management, smoking cessation, dietary changes, weight loss, and physical activity among young adults[5,6].Underdeveloped countries are not adopting mHealth at the anticipated rate despite its benefits[7.] Nsor-Anabiah *et al.*[8] addressed barriers and opportunities for adopting mHealth in countries with limited resources. Bhattacharya *et al.*[9] conducted a study in India, showing that when implemented effectively, mobile health can significantly transform healthcare delivery. The implementation of digital health resources can facilitate humanitarian efforts toward advancing SDG 3 target [10]. In low and middle-income countries, mHealth enhances healthcare by addressing challenges like geographical barriers and resource limitations. As governments recognise mHealth's benefits in meeting health system targets, including the Sustainable Development Goals (SDGs), mHealth has grown in popularity in developing nations [11]. In 2024, 63.13% of India's population lived in rural areas, according to World Bank data. The changing environment and demographics are adding to the public health burden. The Indian government has introduced ICT-based initiatives to enhance healthcare delivery to rural areas[12]. India, as the second-largest smartphone market globally, presents enormous opportunities for mHealth[13].

The justification for implementing mHealth in Delhi-NCR lies in its ability to provide an efficient, cost-effective solution to healthcare issues, especially for at-risk populations. Delhi NCR serves as a major urban health hub with a varied population and specialised medical facilities. These hospitals draw patients from

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surrounding rural areas. The region maintains links with rural communities through outreach programs and national healthcare frameworks, such as the National Health Mission and Ayushman Bharat, integrating urban and rural healthcare needs. The present study is directed by the UTAUT model to investigate the subsequent research questions.

Research Questions

1. What is the level of mHealth adoption in the Delhi NCR region?
2. What factors influence healthcare professionals' willingness to adopt mHealth?
3. How are the factors influencing mHealth adoption?
4. In what ways do demographic factors, such as age, gender, experience, education, and occupation, influence the willingness to utilise mHealth services?

LITERATURE REVIEW

Health care access is a fundamental human right. mHealth and spatial studies integrate mobile technology with geographic information systems (GIS) to address public health challenges by examining how location influences health outcomes[14]. This enables the analysis of health data to map diseases, assess healthcare accessibility, and monitor public health trends [15]. Chandran and Roy[14] showed that digital health technologies offer reduced costs and enhanced accessibility. However, disparities in information and communication technology (ICT) access create a "digital divide" affecting rural, lower socioeconomic, and elderly populations[16]. Jayaprakash *et al.*[17], examined spatial health disparities, focusing on COVID-19's impact on healthcare access in India using the Healthcare Access Index (HAI) and Healthcare Inequality Index (HII). The report advocates for increased healthcare expenditure and improved infrastructure. The literature shows extensive mHealth research using the “Diffusion of innovations theory," "Technology acceptance model (TAM),” and "Unified theory of acceptance and use of technology (UTAUT)" as key theoretical frameworks for mHealth acceptance[18,19,7,12]. Azam *et al.*[10] investigated factors influencing medical professionals' mHealth adoption using UTAUT. Research indicates that mHealth can enhance access to quality healthcare resources and services while reducing costs and improving healthcare delivery. Semiz BB, Semiz T.[20] revealed key constructs, hedonic incentive, habit, and perceived trust influence mHealth adoption. Alam *et al.*[21] found that performance expectations, social influence, and perceived reliability affect mHealth adoption in Bangladesh. The study suggested that mHealth apps should be designed to be more user-friendly and accessible. Research conducted by Cajita *et al* [22]. revealed older people's intentions to use mobile health include prior experience with mobile technology, a readiness to learn about mHealth, the perceived utility and usability of technology, appropriate training, and a doctor's recommendation Nezamdost *et al.*[23] conducted a study integrating TAM and the “Diffusion of Innovation model” to determine the predictors influencing nurses' usage of health-related mobile applications in patient interaction and education. Mensah *et al.* [24] explored how mobile "self-efficacy" influences health services acceptance in China using the "UTAUT model." Their research enhances understanding of mobile health adoption and guides service providers to improve citizens' mobile self-efficacy. Wallis *et al.*[25] examined privacy concerns and usability preferences in mobile health applications, finding that integrating privacy safeguards with user-friendly designs builds trust. Shojaei *et al.*[26] found that mHealth apps need strong privacy protections and intuitive interfaces to increase user adoption.

In the present study, the author attempts to identify the factors affecting healthcare providers' intent to adopt mHealth technology, assess its level of adoption, and the influence of demographics in the Delhi NCR area.

Theoretical framework and hypothesis development

The UTAUT model integrates eight well-known previous models.This integration enhances the UTAUT model's predictive accuracy to 70%. The current study is based on the UTAUT framework (Fig.1), which suggests that “performance expectancy” (PE), “effort expectancy” (EE), “facilitating conditions” (FC), “social influence” (SI), and “behavioral intention” (BI) are key factors influencing the adoption of mHealth. Basic UTAUT model modified by incorporating additional moderating factors, profession, and education, alongside the existing factors of gender, age, and experience.

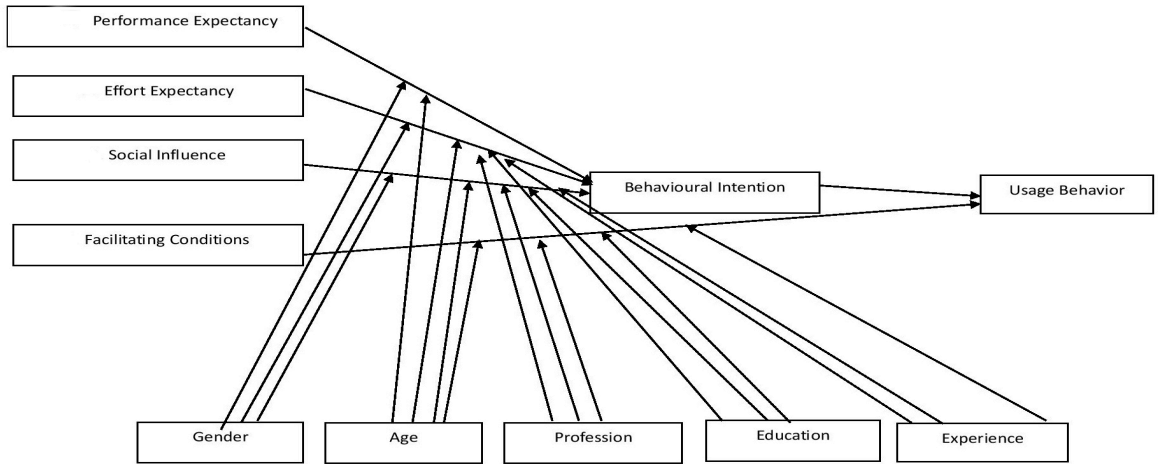

Fig1 Proposed research model for adoption mHealth by healthcare professionals

In the upcoming section, the constructs used in the research conceptual model and hypothesis are examined.

Performance Expectancy (PE)

Venkatesh *et al.* (2003) described "performance expectancy" (PE) as the belief that technology can enhance an individual's work efficiency. PE has been consistently recognized as a strong indicator of mHealth technology acceptance in numerous studies [10,27]. Based on this, the following hypothesis was developed.

Hypothesis 1(H1*): "Performance expectancy (PE) has a significant positive influence on the behavioral intention of healthcare professionals to adopt mHealth".*

Effort Expectancy (EE)

The concept of "effort expectancy" (EE) evaluates how easily a user can grasp and utilize a new technology. Studies have shown EE has a direct impact on individuals' willingness to adopt new technologies [28,29]. Consequently, the hypothesis developed is as follows.

Hypothesis 2 (H2*)*: *"Effort expectancy" (EE) has a significant positive influence on the behavioral intention of healthcare professionals to adopt mHealth*.

Social Influence (SI)

Venkatesh *et al.* (2003) described "social influence" as the extent to which an individual recognizes the impact of other people and is motivated to embrace the new technology [30]. The proposed hypothesis is as follows.

Hypothesis 3 (H3): *"Social Influence" (SI) has a significant positive influence on the behavioral intention of healthcare professionals to adopt mHealth.*

Facilitating Conditions (FCs)

Numerous studies have found that FCs are a highly reliable indicator of technological adoption [31,32.] Thus, we hypothesize:

Hypothesis 4 (H4):*The intention to use mHealth is positively and significantly correlated with the facilitating conditions.*

Behavioral Intention (BI)

Research has demonstrated a positive correlation between behavioral intention and actual behavior[21,30].This suggests that individuals are likely to act upon their intentions to adopt mHealth. Therefore, the following hypothesis is proposed:

Hypothesis 5 (H5): *"Behavioral intention" serves as a statistically "significant" indicator of the usage behavior associated with mHealth.*

Moderating effect

The study is conducted to analyse the moderating effects of age, gender, experience, education, and profession.

METHODOLOGY

Research Design

The current study employed an exploratory and descriptive research design. To tackle the primary concerns of the investigation, data were gathered using a cross-sectional research method. This chosen design facilitated a comprehensive exploration and analysis of all facets of the study.

Target Population

A cross-sectional study was undertaken in public, private, and self-owned hospitals located in the Delhi NCR region during the period from February to April 2024. Data collected through convenience sampling using Google Forms, distributed through personal visits to the clinics, as well as via WhatsApp and emails. The study sample comprised 389 doctors and nurses.

Survey Questionnaire

The questionnaire was designed by selecting items from the study of extant literature and assessed using a five-point Likert scale. A pilot study with a sample of forty respondents was carried out to evaluate the reliability of the questionnaire. The average Cronbach's

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alpha value of 0.877 indicates high internal consistency and strong reliability of the scale.

Data Analysis

Data analysis was performed using SPSS and "Structural Equation Modelling (SEM)," which involves assessing both measurement and structural models. This method explores the connections between latent and observable variables by utilising regression and factor analysis principles. "Measurement models" link latent variables to indicators, while "structural models" define the relationships between constructs. The measurement model employs "Confirmatory Factor Analysis" to evaluate reliability and validity.

RESULTS

Demographic Data of Healthcare Professional

The sample included 389 participants (51.9% males, 48.1% females). Table 1 shows the demographic data of healthcare professionals.

Factors Influencing mHealth Adoption by Healthcare Professionals

The constructs include “Performance Expectancy” (PE), “Effort Expectancy” (EE), “Social Influence” (SI), “Behavioral intention” (BI), “Facilitating Conditions” (FC), and “Usage Behaviour” (UB). A “five-point Likert scale” (1=strongly disagree to 5=strongly agree) measures survey statements. A pilot study with 40 respondents evaluated questionnaire reliability. Cronbach's alpha values ranged from .837to .892, meeting consistency criteria (Hair *et al.*, 2009). Table II shows factors influencing mHealth adoption, with associated statements, Cronbach's alpha values, mean scores, and factor loading.

Table1: Demographic Information of Healthcare Professionals

Demographics	Categories	Frequency	Percentage
Gender	Male	202	51.9
	Female	187	48.1
Age	Below 30 years	66	17.0
	31-40 years	199	51.2
	Above 40 years	124	31.9
Education	Undergraduate	95	24.4
	Postgraduate	250	64.3
	Others	44	11.3
Profession	Nurse	120	30.8
	Doctor	269	69.2
Occupation	Private	213	54.8
	Government	136	35.0
	Own clinic	40	10.3
Experience	1-5 years	89	22.9
	6-10 Years	129	33.2
	11-16 Years	114	29.3
	17 Years and above	57	14.7

Table II: Factors Influencing mHealth Adoption by Healthcare Professionals

Sr. No.	**Factors of mHealth Adoption**	**Factor Loading**	**Mean Score**
Factor 1- Performance expectancy (Cronbach's alpha = 0.892)			3.997

Statement-1	Mobile applications enhance my effectiveness by providing timely advice to patients.	0.837	
Statement-2	Mobile applications improve my clinic's performance.	0.840	
Statement-3	Mobile applications help me accomplish daily tasks more quickly.	0.804	
Statement-4	Mobile health applications allow healthcare professionals to be easily accessible and thereby enhance patient experience.	0.789	
Statement-5	Mobile health applications can reduce a considerable amount of hospital expenses in the provision of healthcare.	0.665	
Factor 2 - Effort expectancy (Cronbach's alpha = 0.868)			4.117
Statement-6	Mobile apps are easy to use.	0.773	
Statement-7	It is easy for me to become skilled at using mobile applications to monitor health issues.	0.819	
Statement-8	Understanding how to interact with mobile applications is clear to me.	0.828	
Statement-9	I do not need any effort to use mobile applications for patient care.	0.736	
Statement-10	I can easily receive, track and evaluate medical data with mobile apps.	0.733	
Factor 3- Social influence (Cronbach's alpha =0.893)			3.895
Statement-11	People who influence my behaviour think that I should use mobile applications to enhance my job effectiveness.	0.840	
Statement-12	People I trust believe that I should use mobile health applications.	0.888	
Statement-13	Peers and colleagues support me in using mHealth applications.	0.858	
Statement-14	The facilities provided by the government / non-government hospital for using mobile applications are easily accessible to me.	0.793	
Statement-15	I have the knowledge necessary to use m Health apps.	0.867	
Statement-16	I have access to the secured and trusted resources necessary to use mobile applications.	0.839	
Statement-17	I can get help from my colleagues when I encounter difficulties using m-Health apps.	0.819	
Factor 5- Behavioral intention (Cronbach's alpha =0.885)			4.236
Statement-18	I intend to use my Health in future.	0.900	
Statement-19	I am interested in improving my skills necessary to incorporate the use of mHealth apps into clinic practice.	0.899	
Statement-20	If m-Health brings convenience to patients and me, I am willing to continue using m-Health apps.	0.879	
Factor 6- usage behaviour (Cronbach's alpha = 0.837)			4.069

Statement-21	I think adoption of mHealth applications will be a pleasant experience.	0.844	
Statement-22	I think mHealth services will provide me with better chances to respond to patients more quickly.	0.884	
Statement-23	I think adopting mHealth will provide me with faster access to patient data.	0.863	
Statement-24	I often use mHealth services.	0.743	

Table III : Construct Reliability and Convergent Validity of Healthcare Professionals

Constructs	Cronbach's alpha	Composite reliability	AVE
Performance expectancy	.892	0.859	0.623
Effort expectancy	.868	0.850	0.607
Social influence	.893	0.845	0.744
Facilitating condition	.889	0.857	0.689
Behavioral Intention	.885	0.876	0.797
Usage behavior	.837	0.877	0.698

Data analysis used “Partial Least Squares Structural Equation Modelling(PLS_SEM)using SMART PLS4. The measurement model was evaluated through “confirmatory factor analysis”(CFA). Construct validity and reliability were assessed using “Cronbach’s alpha”, “composite reliability” and “ Average Variance Extracted”(AVE).

Reliability analysis

The two commonly used methods for establishing reliability include measurement of Cronbach's alpha value and Composite Reliability (rho A). Table III reveals that the Cronbach's alpha scores in this study ranged from 0.837 to 0.892, demonstrating strong internal consistency and high reliability of the research instrument. Scores of 0.7 or higher are deemed satisfactory. Similar to Cronbach's alpha, Composite Reliability offers a more precise assessment of construct reliability. Table III shows that all constructs have Composite Reliability values exceeding 0.7, specifically between 0.845 and 0.877, which confirms the constructs' high reliability.

Validity Analysis

Construct validity measures how well a research instrument evaluates its intended concept through convergent and discriminant validity. Convergent validity shows how different methods measuring the same concept align with each other (Begozzi *et al.*, 1991). Convergent validity is assessed using “Average Variance Extracted” (AVE), considered adequate at 0.5 or above. Table III shows AVE values of 0.607 to 0.797, exceeding acceptable limits and indicating strong convergent validity. Discriminant validity measures how distinct concepts differ from each other, using two approaches.

Fornell and Larcker's- Criterion for Discriminant Validity

Table IV demonstrates that the square root of AVE for each construct is greater than its correlations with other constructs. This indicates that each construct within the model possesses strong discriminant validity, signifying that the constructs are unique and the items effectively assess the appropriate constructs.

Cross-Loadings

Cross-loadings evaluate the discriminant validity of constructs by identifying item associations with constructs. Low cross-loadings indicates strong discriminant validity (Wasko & Faraj, 2005; Hair *et al.*, 2011). Table V shows that factor loadings are higher for respective constructs than for other constructs, verifying robust discriminant validity.

Model Fit Indices

“The Standardized Root Mean Square Residual” (SRMR) is 0.055 for saturated and 0.066 for estimated models, both within acceptable ranges (Steiger, 1990; Steiger & Lind, 1980). The Unweighted Least Squares discrepancy (d ULS) shows a better fit for the saturated model (1.299) versus the estimated model (1.868). Geodesic discrepancy (dG) was 0.552 and 0.636, respectively. Chi-square values were 1239.423 and 1409.002, while the Normed Fit Index (NFI) was higher for saturated (0.811) than estimated (0.785). These indices indicate that the saturated model provides a better data fit.

Table IV:Discriminant Validity						
Constructs	Performance expectancy	Effort expectancy	Social influence	Facilitating condition	Behavior Intention	Usage behavior
Performance expectancy	**0.790**					
Effort expectancy	0.721	**0.779**				
Social influence	0.678	0.697	**0.862**			
Facilitating condition	0.604	0.757	0.750	**0.830**		
Behavior Intention	0.664	0.688	0.626	0.673	**0.893**	
Usage behavior	0.585	0.488	0.441	0.458	0.501	**0.835**

Table V: Discriminant Validity - Cross Loadings						
	BI	**EE**	**FC**	**PE**	**SI**	**UB**
BI1	**0.901**	0.665	0.629	0.617	0.609	0.461
BI2	**0.896**	0.584	0.585	0.555	0.537	O.490
BI3	**0.881**	0.590	0.585	0.603	0.525	0.387
EE1	0.516	**0.773**	0.538	0.577	0.529	0.410
EE2	0.639	**0.819**	0.637	0.637	0.615	O.426
EE3	0.574	**0.828**	0.637	0.535	0.528	0.383
EE4	0.441	**0.736**	0.555	0.496	0.501	O.318
EE5	0.477	**0.733**	0.572	0.554	0.533	0.349
FC1	0.502	0.599	**0.793**	0.532	0.673	0.348
FC2	0.576	0.676	**0.867**	0.517	0.614	0.410
FC3	0.573	0.651	**0.839**	0.498	0.620	0.328
FC4	0.577	0.589	**0.819**	0.463	0.622	0.419
PE1	0.557	0.583	0.504	**0.837**	0.523	0.650
PE2	0.582	0.597	0.517	**0.840**	0.589	0.510
PE3	0.538	0.564	0.444	**0.804**	0.536	0.389
PE4	0.519	0.574	0.464	**0.789**	0.522	0.371
PE5	0.405	0.537	0.459	**0.665**	0.513	0.369
SI1	0.452	0.574	0.593	0.595	**0.840**	0.327
SI2	0.522	0.592	0.633	0.600	**0.888**	0.372
SI3	0.619	0.630	0.699	0.565	**0.858**	0.427
UB1	0.439	0.446	0.451	0.555	0.408	**0.845**

UB2	0.483	0.454	0.426	0.492	0.422	**0.884**
UB3	0.407	0.360	0.335	0.430	0.307	**0.862**
UB4	0.316	0.353	0.288	0.476	0.315	**0.742**

mHealth Adoption Level

Table II shows six factors that influence mHealth adoption by healthcare professionals and their mean values. The adoption level is represented by the overall mean value of the factors as 4.048, indicating that the adoption of mHealth by doctors and nurses is good. The most important factor contributing to the adoption of mHealth is behavioural intention.

Assessment of the "Structural Model"

The analysis of the "structural model," which encompassed the testing of theoretical hypotheses and the examination of relationships between latent variables utilizing the SEM method and "Smart PLS" software.Figure (II) shows the structural model produced with the SmartPLS program. Table VI shows the outcomes of hypothesis testing.

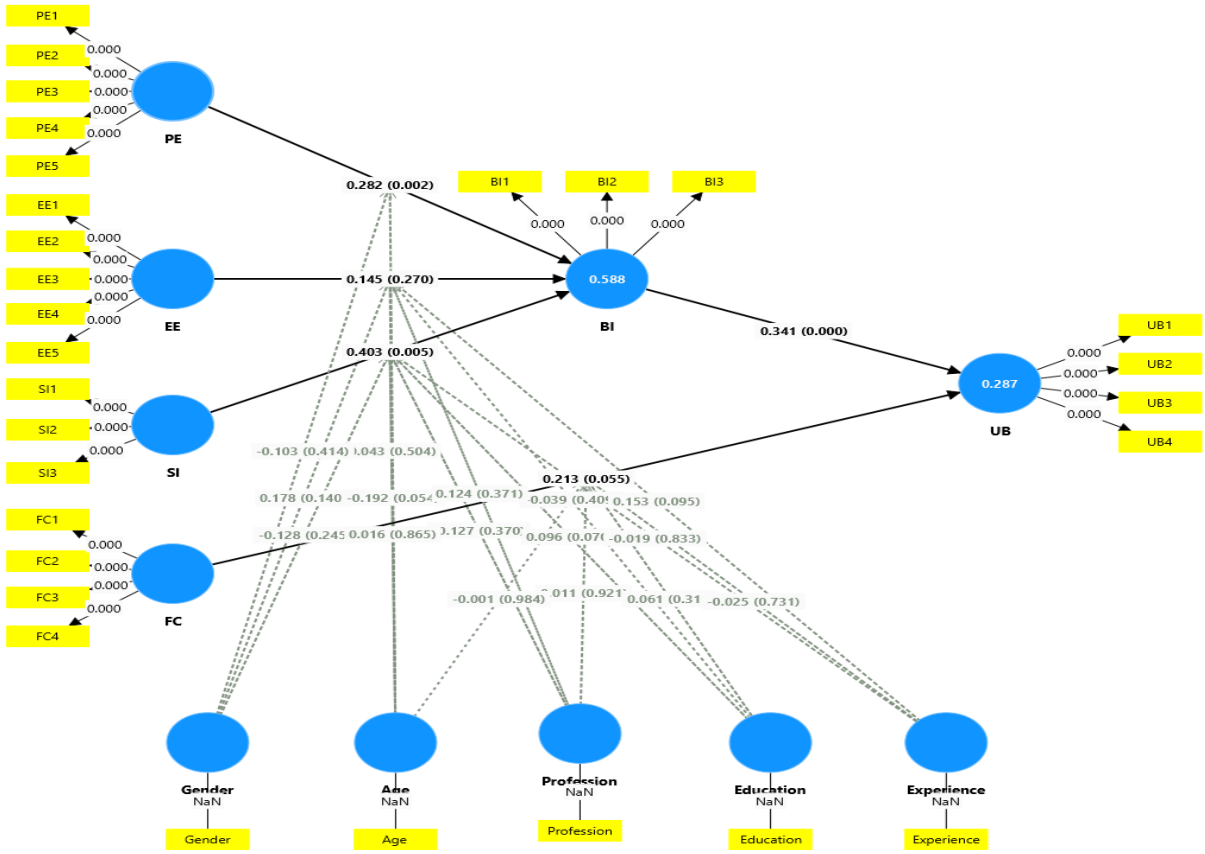

Figure 2 : The Structural Model

Table VI: Outcome of Hypothesis Testing of Healthcare Professionals

Hypothesis		β-value	Sample mean (M)	Standard deviation	T Value	P Value (Significance)	Result
H1	Performance expectancy (PE) has a significant positive influence on the behavioral intention of healthcare professionals to adopt mHealth.	0.282	0.292	0.091	3.117	**.002***	Supported
H2	Effort expectancy (EE) has a significant positive influence on the behavioral intention of	0.145	0138	0.131	0.103	0.270	Not-Supported

	healthcare professionals to adopt mHealth.						
H3	Social Influence (SI) has a significant positive influence on the behavioral intention of healthcare professionals to adopt mHealth.	0.403	0.393	0.144	2.799	**0.005***	Supported
H4	Facilitating conditions (FCs) have a significant positive influence on the usage behaviour of healthcare professionals to adopt mHealth.	0.213	0.212	0.111	1.916	0.055	Not-Supported
H5	Behavioral intention (BI) has a significant positive influence on healthcare professionals' usage behaviour to adopt mHealth.	0.341	0.338	0.073	4.676	**0.000***	**Supported**

Table VII: Showing the Results of Moderators

	Original sample	Sample mean	Standard deviation	T-statistics	P values
Age x PE -> BI	0.043	0.033	0.064	0.668	0.504
Age x FC -> UB	-0.001	0.004	0.063	0.020	0.984
Gender x PE -> BI	-0.103	-0.119	0.126	0.816	0.414
Gender x SI -> BI	-0.128	-0.122	0.110	1.163	0.245
Profession x SI -> BI	-0.127	-0.120	0.141	0.896	0.370
Education x EE -> BI	-0.039	-0.039	0.047	0.826	0.409
Profession x FC -> UB	0.011	0.014	0.116	0.099	0.921
Experience x FC -> UB	-0.025	-0.024	0.072	0.344	0.731
Profession x EE -> BI	0.124	0.118	0.139	0.895	0.371
Education x FC -> UB	0.061	0.056	0.060	1.014	0.311
Gender x EE -> BI	0.178	0.190	0.121	1.475	0.140
Experience x EE -> BI	0.153	0.150	0.092	1.670	0.095
Age x EE -> BI	-0.192	-0.184	0.100	1.924	0.054
Education x SI -> BI	0.096	0.100	0.053	1.811	0.070
Experience x SI -> BI	-0.019	-0.020	0.092	0.211	0.833
Age x SI -> BI	0.016	0.019	0.095	0.171	0.865

Discussion

The mean value of the adoption level (4.048) indicates good mHealth adoption by doctors and nurses. The key factors are behavioral intention, effort expectancy, usage behavior, performance expectancy, facilitating conditions, and social influence. The UTAUT model uses behavioral intention to predict mHealth adoption. The R-square values for BI and UB are 0.588 and 0.287, respectively, predicting 58.8% of behavioral intention and 28% of usage behavior. "Social influence

" has the strongest positive effect on HCPs' behavioral intention (β = 0.403, p=0.05), showing that colleagues and leaders' views strongly affect mHealth adoption. Similar findings were reported by Quaosar *et al.*[33] Hoque and Sorwar [27], and Gao and Luo[31],although Lee *et al.*[7] found no such influence. "Performance expectancy " is the second most important factor (β = 0.282,p = 0.002), indicating that perceived performance benefits increase adoption likelihood, as confirmed by other studies [37]. The results suggest that if individuals believe that using mHealth applications will effectively improve their performance, their likelihood of embracing the system is higher.

According to Davis *et al.* (1989), consumers tend to favor applications that are user-friendly and offer substantial benefits. This preference aligns with the concept of "Effort Expectancy," which Venkatesh *et al.* (2003) define as the ease with which a system can be utilized and managed. However, in the current study, the relationship between "effort expectancy" and the intention to use mHealth is not statistically significant (p = 0.270), similar to Lee *et al.*'s (2021) findings. Concerning the complexity and ease of use of mHealth applications, it is observed that these factors do not significantly influence healthcare professionals in the Delhi NCR region. Effort expectancy does not impact behaviour intention, probably because people of Delhi NCR are more technology friendly. Facilitating conditions including device access and resources, show an insignificant influence on usage behavior (p = 0.055), contrary to the findings of Garavand *et al.*[35] and Galura *et al.*[36]. This indicates a pattern where facilitating conditions hold some importance, though they are not statistically significant. Usage behavior and behavioral intention showed a strong positive correlation (p = 0.000). This result generally supports the conclusion that people with a stronger intention to engage in a behavior are significantly more likely to enact it.

The analysis showed that age, gender, education, profession, and experience did not significantly moderate the relationships between "performance expectancy," "effort expectancy," "social influence, " and "behavior intention," or between "facilitating conditions" and "usage behavior " of mHealth among healthcare professionals. The absence of notable moderation indicates that elements, such as age, experience, or profession, do not fundamentally change how these constructs influence the intention to use mHealth. Consequently, initiatives to boost mHealth adoption should emphasise the technology's usefulness for all professionals, rather than developing strategies based on moderating factors. However, some studies have shown the influence of moderating factors on mHealth adoption [37,38].

Implications

This study identified behavioral intention as the primary determinant of mHealth adoption. Social influence most significantly shapes healthcare professionals' (HCPs) behavioral intentions. Endorsements from scientific societies, healthcare institutions, or senior colleagues can motivate professionals and patients to embrace mHealth. Performance expectancy is the second factor influencing HCPs' intention to adopt mHealth. Emphasising mHealth benefits can motivate both patients and HCPs to utilise this technology. Caregiver counselling can encourage patient engagement with mHealth applications. Providers should focus on refining product design through single-click functionality and a simplified, user-friendly interface.

Conclusion

This study examined the factors determining mobile health (mHealth) usage by HCPs in Delhi NCR using the "Unified Theory of Acceptance and Use of Technology" (UTAUT) model. This study expands our knowledge of mHealth acceptance in India. "Social influence" and "performance expectancy" are key determinants affecting HCPs ' intentions to adopt mHealth. The intention to embrace mHealth positively impacts actual adoption behaviour. The model accounts for 58.8% of behavioural intention and 28% of usage behaviour for mHealth apps. Age, gender, education, profession, and experience showed insignificant influence on mHealth adoption intention. These findings provide insights into mHealth adoption strategies.

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Data availability statement Data

Data is available from the corresponding author(Manav Khatta).

Conflict of interest (COI)

Authors have no conflict of interest.

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