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DOES MHEALTH SERVICES WORTH IN INDIA? A STUDY WITH REFERENCE TO GUJARAT STATE

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Abstract

In today's digital era, the healthcare sector is increasingly adopting innovative technologies to enhance patient experiences. However, in India, especially in Gujarat, mobile health (mHealth) adoption is still developing. A study conducted with 426 respondents using electronic devices for health monitoring identified key factors affecting mHealth adoption. Using Exploratory Factor Analysis (EFA) and multiple regression, the research found that performance expectancy was the most significant factor in mHealth adoption, while perceived intrusion had minimal impact. Additionally, waiting time did not significantly affect adoption. These findings suggest that improving performance expectancy should be a priority for healthcare providers to enhance mHealth adoption, effectiveness, and overall patient care in the digital healthcare landscape.

Key Words: *Digital health, E-Health, M-Health, Technology in Health, Telemedicine*

INTRODUCTION

India faces significant challenges in healthcare, with notable disparities in quality and accessibility across different regions. According to the Global Burden of Disease, India ranks 145th out of 194 countries for healthcare quality, with its Healthcare Access and Quality (HAQ) score at 41.2 in 2016, showing some improvement over the years (Yadavar, 2019). However, substantial gaps persist, particularly between rural and urban areas. For example, Kerala has one of the lowest infant mortality rates in the country, while Uttar Pradesh faces much higher rates. Additionally, despite overall improvements in life expectancy and reduced infant and maternal mortality rates, state-wise disparities remain a challenge. Heart disease, pulmonary disease, and lower respiratory infections are some of the leading causes of years lost due to disability (DALY) in India (Rosling, 2019). In this context, mobile health (mHealth) technologies present a promising solution to bridge these gaps and improve healthcare delivery. mHealth, which leverages mobile phones, wearables, and other digital tools, can empower individuals to manage their health more effectively and provide healthcare access to underserved populations. Digital health, which integrates various digital technologies into healthcare systems, offers the potential to enhance the efficiency, personalization, and precision of healthcare delivery. However, despite its promise, the adoption of mHealth technologies in India is hindered by several factors, including access to technology, education, and awareness, particularly in rural and tribal areas.

This study focuses on understanding the factors that affect the adoption and success of mobile health (mHealth) services in India. It examines the challenges faced by both individuals and healthcare professionals across different regions of the country. The research identifies the major barriers that limit the use of mHealth services and discusses practical strategies to improve their accessibility, usability, and effectiveness. By doing so, the study aims to show how mobile health solutions can better address India's healthcare needs and help overcome existing healthcare challenges.

LITERATURE REVIEW

The adoption and effectiveness of mobile health (mHealth) services have been widely studied across various regions, revealing several key factors that influence user acceptance. Deng, et. al (2014) differentiated mHealth adoption among middle-aged and older adults in China, using the Value Behavior Model and the Theory of Planned Behavior, and found that attitude was the most significant factor. Similarly, Shareef, et. al. (2014) used the Technology Acceptance Model (TAM) in Bangladesh and identified perceived ease of use, perceived usefulness, security, and reliability as key determinants of mHealth adoption. In Bangladesh, Hoque, et. al. (2015) also applied TAM and found perceived ease of use and perceived usefulness as essential factors influencing mHealth adoption. Hoque & Sorwar (2017) confirmed the relevance of the Unified Theory of Acceptance and Use of Technology

(UTAUT) in explaining mHealth adoption among the elderly in developing countries. In Finland, Nikou, S. (2015) highlighted that ease of use, interface design, and willingness to pay significantly impact the attitudes and intentions of older adults aged 60–75 years. Currie (2016) compared mobile health adoption across countries and found that France led in mobile technology adoption, while the USA faced barriers due to strict regulations. Chigona, et. al., (2017) studied the use of mobile phones in improving maternal health in Malawi, revealing that contextual factor, such as social, environmental, and personal circumstances, affect health outcomes. Emmanuel, et. al. (2016) emphasized the importance of socio-materiality in mHealth adoption in rural Nigeria, demonstrating the interdependency between social and technical factors in expanding mHealth services.

Ndayizigamiye & Maharaj (2017) applied the Diffusion of Innovation (DOI) theory to examine mHealth adoption in Burundi, finding that relative advantage, trialability, compatibility, and observability positively influenced adoption among healthcare professionals. In Bangladesh, Nabila et. al. (2019) used UTAUT and UTAUT2 models and found that facilitating conditions were the most significant factor influencing mHealth adoption.

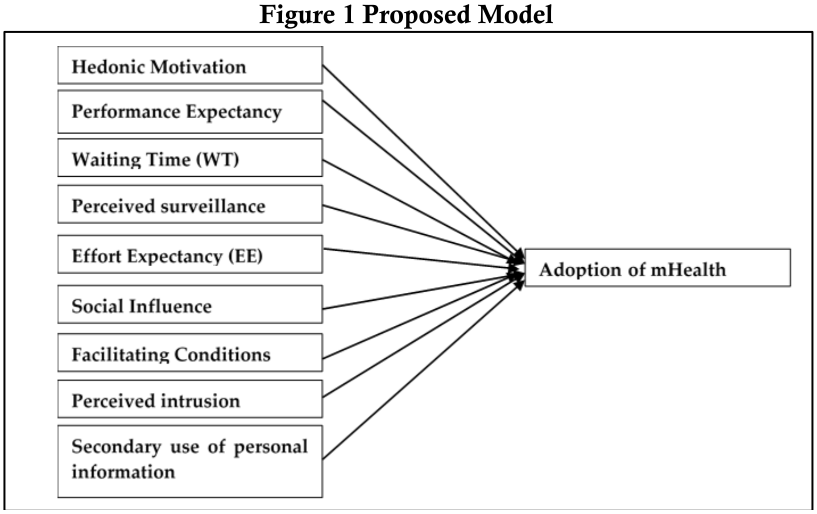
Studies in China, such as Rui, et al. (2017) and Yang Zhao, (2018), highlighted that perceived ease of use, perceived usefulness, subjective norms, and network effects are critical in shaping mHealth adoption. Similarly, Ibukun, et. al. (2018) found that mHealth solutions are most effective when perceived as useful and easy to use, especially in low- and middle-income countries. According to surveys by Deloitte (2018) and Accenture (2018), the use of wearable devices and mobile health apps has increased, with many individuals willing to share health information with healthcare providers. Alam et. al. (2020) found that user satisfaction, perceived value, and factors like trust and e-health literacy significantly influence mHealth adoption. These elements, along with self-efficacy, shape continued usage, with regional and demographic variations.

Hypothesis and Proposed Model:

This study examines key factors affecting the adoption of mobile health (mHealth) technologies in Gujarat, India, focusing on hedonic motivation, performance expectancy, waiting times, privacy concerns, and ease of use. It also explores the role of social influence, facilitating conditions, and psychological factors such as perceived intrusion and the secondary use of personal information.

H1 – Hedonic Motivation significantly affect adoption of mHealth in Gujarat state.
H2 – Performance Expectancy significantly affect adoption of mHealth in Gujarat state.
H3 –Waiting Time significantly affect adoption of mHealth in Gujarat state.
H4 –Percieved Survillance significantly affect adoption of mHealth in Gujarat state.
H5 – Effort Expectancy significantly affect adoption of mHealth in Gujarat state.
H6 – Social Influence significantly affect adoption of mHealth in Gujarat state.
H7 – Facilitating Conditions significantly affect adoption of mHealth in Gujarat state.
H8 – Percieved intrusion significantly affect adoption of mHealth in Gujarat state.
H9 – Secondary use of personal information significantly affect adoption of mHealth in Gujarat state.

Figure 1 Proposed Model



[*Source: Researcher Own Generated*]

RESEARCH METHODOLOGY

Research design

A Quantitative approach is used to explore mHealth adoption in India. Data was collected through a structured questionnaire, focusing on user motivations and challenges. A diverse sample was gathered using online convenience and snowball sampling methods.

Data collection

The study gathered data from 426 respondents of various age groups in Gujarat, using Google Forms and structured questionnaires. Participants were surveyed about their use of mobile health (mHealth) services, including technologies like smartwatches, online health check-up apps, telehealth services, and other mHealth solutions.

Data Analysis:

This study used SPSS 25 to test research hypotheses. Descriptive statistics were applied to analyse demographic data. Exploratory Factor Analysis (EFA) identified key factors influencing mHealth adoption, while Multiple Regression Analysis assessed their impact.

RESULTS AND INTERPRETATION

Descriptive analysis:

The descriptive analysis of the respondents' demographics reveals that most participants are male, primarily aged between 21 and 40 years. The majority have a graduate-level education, with a significant portion being married. Additionally, most respondents report an annual income between 200,001 and 500,000. This overview highlights the key demographic characteristics of the sample, including age, gender, education, marital status, and income level.

Table 1 Demographic information of the respondents

Demographic Variable		Frequency	Percentage
Gender	Male	351	82.4
	Female	75	17.6
Age	Under 20	26	6.1
	21-40	340	79.8
	41-60	52	12.2
	above 60	8	1.9
Education	SSC	23	4.4
	Graduation	153	29.5
	Post-Graduation	332	64.1
	Other (PhD, ITI, Diploma etc.)	10	1.9
Annual Income	Less than 2,00,000	51	12.0
	2,00,001 to 5,00,000	198	46.5
	5,00,001 to 10,00,000	132	31.0
	More than 10,00,000	45	10.6
Marital Status	Married	297	69.7
	Unmarried	129	30.3

[*Source: Researcher Own Generated*]

Reliability and Validity test:

To evaluate the reliability and validity of the variables, Cronbach's Alpha and the KMO test were employed. Cronbach's Alpha values above the 0.6 threshold confirmed the reliability of the variables. Additionally, Exploratory Factor Analysis (EFA) was performed to identify the most and least impactful factors by revealing the underlying relationships between the measured variables.

Table 2 Reliability

Sr. No.	Constructs	No. of Statements	Cronbach's Alpha
1	Hedonic Motivation	3	0.829
2	Performance Expectancy	6	0.808
3	Waiting Time	3	0.873
4	Percieved Survillance	3	0.722
5	Effort Expectancy	5	0.724
6	Social Influence	5	0.719
7	Facilitating Conditions	6	0.723
8	Percieved intrusion	3	0.726
9	Secondary use of personal information	3	0.853
10	mHealth	6	0.735

[*Source: Researcher Own Generated*]

The KMO (Kaiser-Meyer-Olkin) measure and Bartlett's test are essential for assessing the suitability of data for Exploratory

Factor Analysis (EFA). A KMO value above 0.6 indicates good sampling adequacy. In this study, the KMO value of 0.868 exceeds the threshold, confirming that the data is highly suitable for EFA and that the relationships between variables are strong. This ensures that the factor analysis will yield reliable and meaningful results, supporting the continuation of the analysis.

Table 3 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.868
Bartlett's Test of Sphericity	Approx. Chi-Square	9482.914
	df	1126
	Sig.	0.000

[*Source: Researcher Own Generated*]

The rotated component matrix reveals the structure of all ten factors, as shown in the table. During the test, some items did not meet the loading criteria and were excluded from further analysis in the EFA. The table clearly indicates that Performance Expectancy is the most influential factor in the adoption and effectiveness of mHealth services, while Social Influence has the least impact on these outcomes.

Table 4 Rotated Component Matrix[a]

		Component									
Factors	**Items**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Performance Expectancy	PE2	0.762									
	PE1	0.709									
	PE3	0.686									
	PE5	0.686									
	PE6	0.682									
	PE4	0.671									
Facilitating Conditions	FC3		0.758								
	FC2		0.695								
	FC1		0.679								
	FC5		0.628								
	FC4		0.554								
	FC6		0.541								
Waiting Time	WT1			0.806							
	WT3			0.769							
	WT2			0.747							
Perceived Surveillance	PS2				0.813						
	PS3				0.781						
	PS1				0.711						
Perceived intrusion	PI1					0.759					
	PI3					0.723					
	PI2					0.618					
Hedonic Motivation	HM1						0.701				
	HM2						0.687				
	HM3						0.657				
Effort Expectancy	EE4							0.756			
	EE1							0.724			
	EE3							0.665			
	EE5							0.624			
	EE2							0.592			
Secondary use of personal information	SUPI2								0.781		
	SUPI3								0.745		
	SUPI1								0.725		
mHealth	MH2									0.706	
	MH1									0.698	
	MH4									0.646	
	MH5									0.849	
	MH6									0.81	
	MH3									0.784	

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Social Influence	SI2										0.753
	SI3										0.695
	SI1										0.665
	SI4										0.798
	SI5										0.777
Extraction Method: Principal Component Analysis.											
Rotation Method: Varimax with Kaiser Normalization.											
a. Rotation converged in 9 iterations.											

[*Source: Researcher Own Generated*]

Using Exploratory Factor Analysis (EFA) with Varimax rotation, the survey questions were categorized into ten factors. Among these, performance expectancy was identified as the most significant factor influencing mHealth adoption, underlining the importance of perceived benefits and effectiveness. On the other hand, social influence was found to have the least impact, indicating that peer recommendations play a minimal role in users' adoption decisions. This demonstrates the varying significance of different factors in shaping mHealth adoption behavior.

Multiple Regression:

A multiple regression analysis was conducted to assess the impact of various factors on the adoption and effectiveness of mobile health (mHealth) services in India, revealing an R-squared value of 0.523. This indicates that 52.3% of the variation in mHealth adoption can be explained by the factors included in the model. Exploratory Factor Analysis (EFA) identified the key factors influencing adoption, with all except waiting time showing significant effects (p-value < 0.05). Performance expectancy emerged as the most influential factor with a standardized beta of 0.319, while perceived surveillance had the least impact, with a beta value of 0.107. These results emphasize the importance of certain factors in mHealth adoption in India.

Table 5 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.618	0.523	0.418	0.37407

[*Source: Researcher Own Generated*]

Table 6 Coefficient[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.837	0.128		7.112	0.000
	Hedonic Motivation	0.196	0.042	0.260	6.04	0.000
	Performance Expectancy	0.093	0.045	0.319	2.456	0.011
	Waiting Time	-0.009	0.046	-0.016	-0.593	0.555
	Perceived Surveillance	0.078	0.045	0.107	2.02	0.035
	Effort Expectancy	0.111	0.047	0.142	2.838	0.004
	Social Influence	0.155	0.045	0.199	4.366	0.000
	Facilitating Conditions	0.109	0.045	0.145	2.946	0.003
	Secondary use of personal information	0.091	0.005	0.173	3.651	0.000
	Perceived intrusion	0.130	0.032	0.163	3.651	0.000
a. Dependent Variable - mHealth						

[*Source: Researcher Own Generated*]

CONCLUSION

This study identified ten key factors influencing mHealth adoption, with performance expectancy emerging as the most significant, followed by waiting time, which negatively impacted adoption. Perceived surveillance had minimal influence on users' adoption decisions. These findings suggest that enhancing performance expectancy and reducing waiting times can boost user engagement with mHealth applications. The results align with previous research, including Mofokeng & Tan (2021), which emphasizes the role of user expectations and experiences in the successful implementation of health technology solutions.

Limitations and implication of the study:

While this study provides valuable insights into mHealth adoption, it has some limitations. As a descriptive study, it relies on observational data, which may limit the depth of its conclusions. The sampling method includes individuals using health monitoring apps or websites but does not account for demographic differences or specific usage contexts. Future research could focus on targeted demographics or geographic regions to improve the applicability of the findings.

Furthermore, mHealth service providers should prioritize accuracy and reliability to build user trust. Incorrect diagnoses or misinterpreted health information can undermine confidence in the applications. Additionally, ensuring a user-friendly and engaging interface is crucial for improving accessibility and minimizing barriers to effective use. By addressing these factors, mHealth providers can enhance user satisfaction and encourage wider adoption of mobile health technologies.

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