



Understanding the Factors Influencing Mobile Health (mHealth) Adoption among Healthcare Professionals in Punjab, Pakistan

Muhammad Omer Hassan¹, Salman Bin Naeem²

¹ Ph.D. Research Scholar, Department of Information Management, The Islamia University of Bahawalpur Pakistan.
Email: omerhassanbaloch@gmail.com

² Professor, Chairman Department of Information Management, The Islamia University of Bahawalpur Pakistan.
Email: salman.naeem@iub.edu.pk

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ABSTRACT

This study was carried out with objectives to identify the predictors of mobile health (mHealth) technology adoption among healthcare professionals in limited-resource settings. study examines the predictors of mHealth adoption among doctors and nurses working in public and private hospitals across South Punjab, Pakistan, using an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT2). A cross-sectional survey was administered to 423 healthcare professionals, and the resulting data were analysed through confirmatory factor analysis (CFA) and structural equation modelling (SEM) across an eleven-construct model comprising Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Self-Concept (SC), Hedonic Motivation, Price Value, Habit, Digital Literacy (DL), Behavioural Intention (BI), Digital Health Adoption (DHA), and Health Disparity Reduction (HDR). The measurement model demonstrated an acceptable fit to the data (RMSEA = 0.033; CFI = 0.925; IFI = 0.926; TLI = 0.915). Results indicate that Effort Expectancy and Digital Literacy were statistically significant positive predictors of Behavioural Intention, while Performance Expectancy, Facilitating Conditions, Hedonic Motivation, Social Influence, Habit, and Price Value did not reach significance. Behavioral Intention, in turn, significantly predicted Digital Health Adoption, which subsequently predicted reductions in health disparity. These findings suggest that, contrary to assumptions embedded in adoption models developed in high-resource settings, perceived usefulness alone is not sufficient to drive mHealth uptake among healthcare professionals in low-resource contexts; ease of use and digital competence carry far greater weight. The study proposes a scientifically proven basis for policymakers, health officers, and technology designers in search of to plan and scale mHealth involvements that meaningfully decrease healthcare access gaps.

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Corresponding Author's Email: omerhassanbaloch@gmail.com

1. Introduction

Mobile health is known as mHealth. This name was first created by Robert Istepanian. It refers to the use of mobile phones and communication networks to deliver healthcare services. The World Health Organization defines mHealth as using mobile devices in medicine and public health. The use of information and communication technology, especially mobile tech, has transformed healthcare delivery. This technology has made healthcare more widely accessible and less expensive. As a part of e-health, healthcare professionals, patients, and organizations are now embracing mobile technology. They use it to produce, communicate, and consume healthcare information and services (Nacinovich, 2011; Rahimi et al., 2018). New challenges in healthcare are being addressed by mHealth solutions, including the rise in chronic diseases, the high cost of current national healthcare, the need to empower patients and families to take responsibility for their own health, and the need to provide immediate access to healthcare services wherever they are needed (Silva et al., 2015). Around the world, telemedicine services are accessible to the general population. Due to the increase in chronic and communicable diseases, developing countries' healthcare systems struggle to deliver better, quicker, and more affordable care (Hersch, 2017). Millions of people die as a result of diseases which are treatable. Every year, 52% of children die from curable diseases like malaria, asthma, and diarrhea. Researchers and policy makers have taken advantage of this widespread usage of mobile phones to use them as a catalyst for healthcare change to address geographic barriers, gaps and inequities in the access and delivery of health services, shortages of health care providers, and excessive health care prices (Fiordelli, Diviani, & Schulz, 2013).

Mobile technology's portability, quick access, and direct interaction enable faster health information sharing, which benefits clinical and public health practices. The characteristics of mobile illustrate mobile health, or mHealth. It has the power to completely change how healthcare is provided worldwide, especially in low- and middle-income countries (World Health Organization, 2011). The idea of mHealth first emerged in 2007. This is the beginning of a completely new paradigm in field of health. The term "mobile health" today refers to all mobile information, communication, and network technologies that allow access to healthcare systems and services (Adibi, 2015). MHealth was referred to as "the biggest technology breakthrough of our time" and its use would "address our greatest national challenge" by US Secretary of Health and Human Services Kathleen Sebelius in 2011 (Steinhubl, Muse, & Topol, 2013). It comprises the mobile devices and accessories that healthcare professionals, patients, and clients use to collect, store, and analyze data for decision-making. Medical and public health practices assisted by portable electronic devices, such as cell phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless gadgets, are referred to as mobile health (mHealth) (World Health Organization, 2011). Despite this recognized potential and the widespread availability of mobile devices, the adoption of mHealth tools by healthcare professionals in low-resource settings remains significantly low. This difference between what mHealth capacities and what it actually carries in practice points to an important, uninvestigated issue. Why adoption has been slow, or has failed outright in many cases, is still not well understood — and part of the difficulty may lie in the tools we use to study it. Most existing technology adoption models were built around high-resource settings, so they may simply miss the socio-technical, economic, and organizational realities that shape. Factors such as a lack of reliable internet connectivity, inadequate technical support, concerns about data privacy and security, and the perceived complexity or lack of relevance of mHealth tools may serve as major barriers (Eapen et al., 2016; Wagstaff et al., 2007).

In developing countries, such as Pakistan, one of the major problems encountered by people is lack of facilities or the high cost of transportation, which is important for mobility from their residence to hospitals or other medical emergencies (Salahuddin & Jalbani, 2006). According to Pakistan Telecommunication Authority (PTA), there are 194 million cellular subscribers, 121 million 3G/4G subscribers, 2 million basic telephony subscribers, and 124 million broadband subscribers in the country in 2022 (*Telecom Indicators | PTA*). Thus, there is a significant opportunity to use various mobile phone services, including call, SMS, and data transfer facilities and mobile apps for disease prevention and health promotion. Silva et al. (2015) highlighted the significance of the Internet and web services that enable virtual face-to-

face meetings between medical professionals and patients. They proposed an architecture of mHealth service where there is a system having web servers holding web services i.e., remote monitoring system, physician user interface, and emergency response at one side, while on the other side, users/patients are having a mobile device, custom and specialized devices, data gathering, health records, medical applications, and wearable sensors. Therefore, there is a compelling need to systematically investigate and model the specific factors that influence the acceptance and sustained use of mHealth applications among healthcare professionals in these unique contexts. Deprived of a strong consideration of these predictors, hard work to project, organize, and scale mHealth involvements will remain to fall short — weakening to change technical potential into perceptible health outcomes for the people who want them most. This study reports this gap by investigating the important predictors of mHealth implementation, present research-based understandings for policymakers, public health organizations, and technology designers.

1.1. Objective of the Study

The aim of the current study is;

1. To identify the predictors of mHealth technology adoption among healthcare professionals (Doctors and Nurses) in low resource settings

2. Literature Review

This study set out to find the key predictors shaping the acceptance of mobile health (mHealth) devices among healthcare specialists in low-resource locations. The literature review part lays out the academic and experiential basics of the research while highlighting gaps in prevailing knowledge on the drivers of mHealth adoption. The World Health Organization (WHO) defines mHealth as the use of mobile devices — including smartphones, tablets, patient intensive care devices, and personal digital assistants (PDAs) — to change current medical and public healthcare exercise (World Health Organization, 2011). The term also covers these devices' dimensions to produce, achieve, access, and deliver data flawlessly among participants, allowing real-time message and collective care road map within healthcare settings (Aker, 2010). Health attractions on both essential mobile structures (voice, SMS, MMS) and more progressive technologies (GPS, Bluetooth, 3G/4G networks) to backing real-time health data spread, remote nursing, and sturdier care connectivity (World Health Organization, 2011). It supports main healthcare delivery done numerous key applications: clinical conclusion care systems that guide diagnosis and treatment during discussions; mhealth archives and data platforms that rationalize service management and delivery; targeted health teaching movements that distribute defensive care information to providers and societies; and protected communication channels that ease teamwork among healthcare teams and real-time patient- engagement (Porter et al., 2016; Rivera Ramirez, 2024).

Health technologies and gadgets — together with mobile phones, digital tablets, wearables, remote monitoring devices, and PDAs — enable healthcare users to produce, store, regain, and exchange data (Selik et al., 2014). These machineries are generally divided into three categories: patient-centered technologies (e.g., self-monitoring apps), doctor-centered tools (e.g., clinical decision-support systems), and patient-doctor communication tools (e.g., telehealth platforms) (Prieto-Avalos et al., 2022). Primary healthcare services are basic healthcare services provided at the local or district level. They are the first point of contact for individuals seeking healthcare. The terms *primary care* and *primary health care* are often used interchangeably (Muldoon, Hogg, & Levitt, 2006). In this study, primary healthcare services include care provided to both individuals and communities. These services are delivered through public and private hospitals and are extended to workplaces and residential areas. This approach is particularly important in low-income and resource-constrained settings, where accessible and nearby healthcare services help improve health outcomes (Muldoon, Hogg, & Levitt, 2006). Gagnon et al. (2016) conducted a 14-year review (2000–2014) and identified factors shaping healthcare professionals' mHealth adoption: perceptions, technical barriers, cost, time constraints, privacy/security risks, tech familiarity, risk-benefit analysis, and workplace dynamics

(colleagues, patients, management). These collectively influence integration into clinical workflows. The authors found that, being key players for providing healthcare services to the patients, healthcare professionals (doctors, nurses and paramedical staff) are most important part of healthcare system across the world. Positive perception, technological knowledge, technical skills and interaction with colleagues, patients and management of hospital have positive and significant impacts on mHealth adoption while cost, time, privacy and security issues were found major challenges in adopting mHealth practices by both patients and healthcare professionals. Eapen et al. (2016) determined the best fit and suitable mHealth roadmap to detect the factors contributing cardiovascular diseases at early stage as well as the curing remedies. The authors analyzed the existing literature and healthcare systems in the perspectives of payer, provider, patient and caregiver. The authors highlighted that mobile devices and apps have the potential to gather valuable data, aiding in informed clinical decision-making. For certain acute and chronic conditions, mHealth can strengthen providers' capacity to intervene proactively by giving patients access to diagnostic tools and information. Ultimately, however, the success of any mHealth solution depends on clinician engagement — software applications on their own cannot treat patients.. Instead, many mHealth products serve to augment healthcare professionals' capabilities, enabling them to deliver optimal care by ensuring the right patient receives the right service at the right time.

3. Research Method

A cross-sectional survey was conducted in public and private hospitals in South Punjab, Pakistan. The population of the study comprised of nurses and doctors working in the South Punjab's tertiary and secondary care hospitals. A two-part questionnaire was developed based on a literature review and an assessment of healthcare facilities' current health delivery, infrastructure, and need for mHealth. Part 1: Captures demographic information (e.g., profession, experience, age, gender, work unit). Part 2: Contains 34 statements across seven sub-scales: Performance Expectancy (6 statements), Effort Expectancy (5 statements), Social Influence (4 statements), Facilitating Conditions (4 statements), Self-Concept (5 statements), Behavioral Intention (5 statements), mHealth Adoption (5 statements) (Appendix-A). The reliability of the questionnaire is measured through Cronbach's alpha. The six statements of the PE received .890 Cronbach's alpha score, the 5-items on EE received .893 score, the four statement of the FC obtained .839 score, the four statements of the SI received .862 score, the SC received the score .885 for five statement of the BI received Cronbach's alpha score .885, and the five statements of the mHealth adoption received .673 score. The overall 34 statements of the questionnaire under seven constructs received Cronbach's alpha value .966, which indicates high reliability of the questionnaire. Data for the present study was collected through purposive sampling. Data was analyzed using 'statistical package for social sciences' (SPSS software v26). Missing values in the dataset was replaced using 'expectation-maximization' (EM) methods. Demographic information analyzed and presented in frequency and percentage. The significant value fixed $p < .05$.

3.1. Demographic Characteristics of the Study Participants

Of the 423 respondents, 264 (60%) were male respondents and 159 (40%) were female respondents. The majority 282 (66%) of the respondents were doctors, and 154 (34%) were nurses. Using Chi-square, researcher has found a statistically non-significant difference in the distribution of males and females among different age groups ($\chi^2 = .744$, $p = .622$, phi's value = 0.34). Similarly, we have found a statistically non-significant difference in the professional experience of male and female respondents ($\chi^2 = 1.398$, $p = 0.674$, phi's value = 0.046). A significant difference was observed between respondents' job profession ($\chi^2 = 1.398$, $p = 0.674$, phi's value = .046). Moreover, we found a non-significant differences in professional experience of gender ($\chi^2 = 1.398$, $p = 0.674$, phi's value = 0.46). However, we have noted a statistically significant difference across different working area of respondents ($\chi^2 = 1.87$ $p = 0.002$, phi's value = .017) (Table 4.1).

Table 1: Demographic Information of the Respondents

Health Professionals	Male	Female	χ^2 Value	p-Value	Phi/ Cramer's V
Age					
Less than 35years	217 (51%)	70 (6%)	.744	.622	0.34
36-50years	65 (15%)	40(12%)			
More than 50 years	20 (4.7%)	11 (2.8%)			
Total	302 (71%)	121 (29%)			
Job Profession					
Doctor	160 (56%)	122 (44%)	1.498	0.037	.020
Nurse	45(29%)	109(71%)			
Total	215 (71%)	124 (29%)			
Professional Experience					
< 5 years	150 (54%)	110 (35%)	1.398	0.674	.046
5-10 years	60(29%)	120 (71%)			
>15 years	15 (47.9%)	10(52.1%)			
Total	220 (71%)	203 (29%)			
Work Area					
Primary healthcare	32 (9.8%)	38 (10.7%)	.187	0.002	0.17
Medical-Surgical	15 (90.2%)	76 (89.3%)			
Intensive Care	24(47.9%)	16 (22.1%)			
Emergency Unit	10(3.5%)	15 (6.8%)			
Operating Unit	12(5.5%)	8(7%)			
Total	226 (71%)	141 (29%)			

3.2. Descriptive Statistics

The data presents a highly positive perception of mHealth adoption across all measured constructs. Respondents overwhelmingly agree with the benefits and express a strong intention to use mHealth technologies.

3.2.1. Performance Expectancy (PE)

Respondents demonstrated very high-performance expectancy, with mean scores ranging from 3.88 to 3.98. They strongly believe mHealth is useful, helps provide timely medical advice, increases clinical performance, and reduces hospital expenses. Notably, 80.9% to 87.5% of respondents agreed or strongly agreed with each statement, indicating a consensus on its utility.

3.2.2. Effort Expectancy (EE)

Perceptions of effort expectancy were generally positive but showed more variation. Respondents found mHealth apps easy to use overall (EE3, $M = 3.83$, 78% Agree/Strongly Agree), but they were less convinced that learning to screen health matters through mHealth is straightforward (EE1, $M = 3.37$), with 23.9% disagreeing. EE4 received a notable level of disagreement (25.1%). This suggests that respondents found the tools easy to use. However, they believed that using these tools in patient care still requires considerable effort.

3.2.3. Facilitating Conditions (FC)

Conditions supporting mHealth use are viewed favourably overall. Respondents feel they have the necessary resources, knowledge, and collegial support to use these tools. The strongest agreement was recorded for institutional encouragement (FC4, $M = 4.04$, 80.4% Agree/Strongly Agree) — a factor widely recognized as a critical facilitator of adoption.

3.2.4. Social Influence (SI)

Social influence toward mHealth adoption is very strong. Item means ranged from 3.86 to 4.01, with over 81% agreement on each item. Respondents believe that influential figures, peers, and mentors within their professional community endorse mHealth use, and that those who use it are perceived as more informed.

3.2.5. Self-Concept (SC)

Personal attitudes toward mHealth are extremely positive. Respondents view mHealth as necessary for clinical practice (SC1, $M = 4.04$) and as evidence-based (SC2, $M = 4.05$). They also

feel their own behaviour aligns with the image associated with mHealth (SC4, $M = 3.97$), pointing to a strong personal alignment with the technology

3.2.6. Behavioral Intention (BI) and mHealth Adoption (MH)

Respondents presented a strong purpose to use mHealth in the future. The mean scores ranged from 3.95 to 4.03. More than 70% of respondents agreed or strongly agreed with all intention statements. This positive intention is reflected in their actual use of mHealth. Respondents described mHealth as a pleasant experience (MH1, $M = 4.01$). They also reported that it provides faster access to data and quicker responses to patients. Many respondents indicated that they spend a considerable amount of time using mHealth applications (MH3, $M = 4.09$). The results indicate a very positive performance expectancy toward mHealth. The mean scores for all five items ranged from 3.89 to 4.07. This shows that respondents believe mHealth is useful in both their clinical practice and daily work. The low standard deviations (0.518–0.661) indicate that these views are consistent across respondents. Most respondents (86.8%) agreed or strongly agreed that mHealth is useful in their daily work (PE1, $M = 3.89$). Similarly, 86.6% believed that mHealth provides timely medical advice (PE2, $M = 3.93$). In addition, 84.6% agreed that it helps them complete daily tasks more quickly (PE3, $M = 3.93$). Respondents also believed that mHealth improves their clinical performance. For PE4, 89.9% agreed or strongly agreed that adopting mHealth enhances their clinical effectiveness ($M = 4.03$). The highest-rated statement was related to cost reduction. About 90.1% agreed or strongly agreed that mHealth can reduce hospital expenses (PE5, $M = 4.07$), indicating strong confidence in its economic benefits.

The findings also show a highly positive effort expectancy toward mHealth. The mean scores ranged from 3.87 to 4.04. Respondents generally found mHealth applications easy to learn, easy to interact with, and easy to use. The low standard deviations (0.620–0.768) indicate that these positive perceptions were shared by most respondents. The data demonstrates an overwhelmingly positive perception of social influence encouraging the use of mHealth. All five statements received very high mean scores (ranging from 3.96 to 4.03 on a 5-point scale), indicating strong agreement that important referent groups including mentors, seniors, colleagues, and the wider professional community support and value the use of mHealth in clinical practice. The low standard deviations (all below 0.62) show a strong consensus among respondents. SI3 & SI5 statements shared the highest mean score of 4.03. SI3 shows that 87.8% of respondents believe that professionals who use mHealth are more informed and active, creating a positive perception of its users. The SI5 indicates that 88.8% feel that people who influence their behaviour think they should use mHealth. SI2 valued opinions with a mean of 3.97, a strong majority (86.1%) agree that people whose opinions they value prefer them to use mHealth. The data reveals an exceptionally strong and positive self-concept regarding mHealth among the respondents. This construct received the highest average scores so far, with means ranging from 4.00 to 4.14. This suggests that healthcare professionals do not merely recognize mHealth's external value — they hold a strong personal belief in, identification with, and confidence in both its necessity and their own ability to use it effectively. The standard deviations were very low (0.57–0.59). This shows a high level of agreement among respondents. Their opinions about mHealth were consistent.

Healthcare professionals recognized that mHealth is useful and easy to use. They also considered it an important part of their professional practice. They believed that mHealth is necessary and supported by evidence. In addition, they expressed strong confidence in its clinical benefits. These positive beliefs support the continued use of mHealth. The results also show a strong intention to use mHealth in the future. The mean scores ranged from 3.85 to 3.96. This indicates a high willingness to adopt and continue using the technology. Respondents were most willing to use mHealth when it offered clear practical benefits. For example, they believed it helps reach patients in rural areas and improves patient convenience. This shows that their intention is based on practical value. Many respondents also wanted to improve their mHealth skills. This reflects a commitment to long-term and effective use. The findings also indicate high levels of mHealth adoption. The mean scores ranged from 3.99 to 4.09. This shows that respondents are already using mHealth and benefiting from it. A higher standard deviation was found for MH3 ($SD = 1.10$). This indicates that the amount of time spent using mHealth differs among respondents.

Overall, the results show a clear shift from intention to actual use. Healthcare professionals are actively using mHealth in their daily practice. They reported benefits such as faster access to information, quicker responses to patients, and a positive user experience. These findings suggest that mHealth has been successfully integrated into the healthcare environment.

Table 2: Descriptive Statistics

Statements	M	SD	D	N	A	SA
PE1	3.88	.457	1(2%)	11(2.6%)	33(7.8%)	370(87.5%)
PE2	3.96	.452	1(.2%)	5(1.2%)	32(7.6%)	359(84.9%)
PE3	3.91	.563	91.2%)	16(3.8%)	33(7.8%)	342(80.9%)
PE4	3.97	.510	0(00%)	14(3.3%)	19(4.5%)	355(83.9%)
PE5	3.98	.561	4(.9%)	10(2.4%)	17(4%)	352(83.2%)
EE1	3.37	.904	5(1.2%)	101(23.9%)	55(13%)	255 (60.3%)
EE2	3.44	.841	5(1.2%)	79(18.7%)	67(15.8%)	269(63.6%)
EE3	3.83	.723	11(2.6%)	17(4%)	34(8%)	330(78%)
EE4	3.44	.939	3(7%)	106(25.1%)	33(7.8%)	262(761.9%)
EE5	3.90	.566	3(.7%)	18(4.3%)	18(4.3%)	362 (85.6%)
FC1	3.86	.620	3(.7%)	23(5.4%)	29(6.9%)	345(81.6%)
FC2	3.71	.728	3(.7%)	49(11.6%)	27(6.4%)	334(79.0%)
FC3	3.80	.632	2(.5%)	33(7.8%)	25(5.9%)	352(83.2%)
FC4	4.04	.562	3(.7%)	9(2.1%)	13(3.19%)	340(80.4%)
SI1	4.00	.472	0(0%)	9(2.1%)	20(4.7%)	356(84.2%)
SI2	4.01	.515	1(.2%)	8(1.9%)	24(5.7%)	343(81.1%)
SI3	3.90	.438	0(0%)	10(2.4%)	33(7.8%)	368(87.0%)
SI4	3.86	.500	1(.2%)	14(3.3%)	39(9.2%)	359(84.9%)
SC1	4.04	.445	1(.2%)	2(.5%)	22(5.2%)	353(83.5%)
SC2	4.05	.501	1(.2%)	5(1.2%)	21(5.0%)	339(80.1%)
SC3	3.79	.591	1(.2%)	7(1.7%)	21(5.0%)	346(81.8%)
SC4	3.97	.593	1(.2%)	32(7.6%)	28(6.6%)	347(82%)
SC5	3.95	.660	8(.5%)	61(4.1%)	126(8.4%)	1092(72.8%)
BI1	4.03	.732	8(.5%)	111(7.4%)	143(9.5%)	1064(70.9%)
B12	3.99	.702	15(1.0%)	79(5.3%)	160(10.7%)	1089(72.6%)
B13	3.98	.639	10(.7%)	46(3.1%)	141(9.4%)	1103(73.5%)
B14	3.95	.660	8(.5%)	61(4.1%)	126(8.4%)	1092(72.8%)
BI1	4.03	.732	8(.5%)	111(7.4%)	143(9.5%)	1064(70.9%)
MH1	4.01	.766	18(1.2%)	80(5.3%)	87(5.8%)	1004(66.9%)
MH2	3.99	.826	48(3.2%)	37(2.5%)	120(8.0%)	973(64.9%)
MH3	4.09	1.10	23(1.5%)	63(4.2%)	88(5.9%)	939(62.6%)
MH4	4.00	.799	33(2.2%)	63(4.2%)	92(6.1%)	996(66.4%)
MH1	4.01	.766	18(1.2%)	80(5.3%)	87(5.8%)	1004(66.9%)

4. Discussion

Our findings validate the findings of a previous study that reported that SI is strongly correlated with SC, BI, and MA (Mohammadzadeh & Safdari, 2014) SC was also positively correlated with BI and MA. There was a moderate-strength positive correlation between BI and MA. However, BI was a strong predictor for MA. The literature also shows that a higher BI level predicts the actual use behavior of mHealth adoption (Burney et al., 2013; Chib et al., 2015). Overall, the goodness-of-fit values showed that the CFA model was acceptable ($\chi^2 = 3.206$; $df = 254$; $p = 0.000$; $RMSEA = 0.084$; $CFI = 0.893$; $IFI = 0.894$; and $TLI = 0.874$). Structural equation modeling (SEM) was applied to validate the hypotheses of this study. The correlational scores indicated that PE was strongly associated with EE, SI, SC, and FCs. The path coefficient estimation showed that PE was positively correlated with BI. Our findings validate the findings of previous studies that EE has a statistically positive significant influence on BI. Similarly (Alharbi, 2014b; Chib et al., 2015; Sidney et al., 2012b). reported a strong correlation between EE and BI. However, in contrast to our findings, (Sidney et al., 2012b) claimed that PE does not significantly influence BI. Our findings support the findings of another study that reported that DL has a statistically positive significant influence on BI, which has a subsequent positive significant influence on DHA. The relationship was supported by MA (Rivera Ramirez, 2024). Moreover, the findings of our study are consistent with the findings of previous study (Sun,2013), that DHA has

a statistically positive significant influence on HDR. The SEM model demonstrated acceptable goodness-of-fit ($\chi^2/df = 3.207$; RMSEA = 0.084; CFI = 0.891; IFI = 0.892; TLI = 0.874), thereby validating the application of the UTAUT model within the study's population of healthcare professionals in low-resource environments. The findings of our study statistically validated four out of ten hypotheses, indicating that EE, DL, BI, and DHA had a statistically significant influence on the BI of healthcare professionals towards mHealth adoption. Previous studies have also indicated a positive Influence of PE on BI (Alaiad, Alsharo, & Alnsour, 2019). On the other hand, PE, FC, SI, HM, HB, and PV have a positive but non-significant influence on BI.

5.1. Implications of the Study

The findings have significant implications for government bodies, health ministries, and regulatory agencies. Evidence-Based National Digital Health Strategy: The model provides empirical evidence to shape effective policies. If the model highlights "Unreliable Connectivity" as a critical barrier, it strengthens the case for policymakers to invest in improving internet infrastructure in rural health facilities. The findings can help policymakers promote mHealth adoption. They can use these results to develop effective policies and strategies.

6. Conclusions of the Study

This study confirms the applicability of an extended UTAUT2 model — one that incorporates the construct of self-concept — for understanding mHealth adoption among doctors and nurses in low-resource settings. The findings show that healthcare professionals' intention to use mHealth is driven primarily by their belief in its performance benefits (performance expectancy) and by their own confidence and professional identity (self-concept), with these effects further moderated by age and gender. Ultimately, the research demonstrates that successful mHealth implementation can serve as a powerful means of bridging healthcare gaps, reducing costs and disparities, and improving the quality of care in underserved settings. In sum, performance expectancy and self-concept emerge as the principal predictors of healthcare professionals' behavioural intention toward mHealth adoption, with age and gender acting as moderating factors. These findings suggest that successful mHealth adoption can drive meaningful improvements in healthcare delivery — including greater access to quality resources, reduced costs, and narrower health disparities — particularly in low-resource settings.

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