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Leveraging the TOE Framework: Examining the Potential of Mobile Health (mHealth) to Mitigate Health Inequalities

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Abstract: (1) Aims and Objectives: Mobile health (mHealth) is increasingly becoming a favorite healthcare delivery solution in underserved areas around the globe. This study aims to identify the influence of technology–organization–environment (TOE) factors on mHealth adoption and to assess the influence of mHealth on the reduction in health disparities in the context of healthcare delivery in low-resource settings. (2) Methods: A cross-sectional survey of physicians and nurses was carried out at six hospitals in the public and private health sectors in Pakistan. The survey's theoretical foundation is based on the technology–organization–environment (TOE) framework. TOE constructs (relative advantage, compatibility, management support, organizational readiness, external support, and government regulations) were used to develop hypotheses. The hypotheses were tested using structural equation modeling (SEM). (3) Results: Findings from this study show that management support and external support are the two main predictors of mHealth adoption among healthcare professionals. The study proposes an mHealth adoption model that can significantly contribute towards improving medical outcomes, reducing inefficiencies, expanding access, lowering costs, raising quality, making medicine more personalized for patients, and gaining advantages from mHealth solutions in order to reduce health disparities. (4) Conclusion: The study suggests that there is no single approach that could support mHealth adoption. Instead, a holistic approach is required that considers cultural, economic, technological, organizational, and environmental factors for successful mHealth adoption in low-resource settings. Our proposed mHealth model offers guidance to policymakers, health organizations, governments, and political leaders to make informed decisions regarding mHealth implementation plans.

Keywords: mHealth adoption; TOE framework; health disparities; healthcare; access

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1. Introduction

Mobile health, abbreviated as mHealth, constitutes a category within electronic health (eHealth). It involves the utilization of wireless and mobile technologies, including smartphones and tablets, to facilitate communication between healthcare providers and individuals (patients), with the aim of enhancing medical care and promoting public health [1]. The National Institute of Health, USA, provides an expansive characterization of mHealth, encompassing a varied range of wireless and mobile technologies aimed at enhancing health research, healthcare services, and overall health results. This categorization extends beyond cell phones to encompass any wireless device carried or worn by individuals that receives or transmits health-related data or information. This includes a diverse array of devices like sensors (such as implantable miniature sensors and "nano-sensors") and monitors (such as wireless accelerometers, blood pressure monitors, and glucose monitors) [2].

The World Health Organization (WHO) has classified mHealth interventions into six types of initiative: (i) facilitating communication between individuals and health services through phone helplines and emergency toll-free numbers; (ii) fostering communication between health services and individuals by disseminating public service messages or announcements, such as promoting general vaccination efforts; (iii) enabling consultation among healthcare workers; for example, in situations where lady health workers (the lady health workers program is an initiative for improving access to healthcare through lady health workers, particularly for women and children in Pakistan) in remote areas seek advice on health issues or problems; (iv) facilitating communication between agencies via mobile phones or handheld portable devices to manage health emergencies; (v) implementing health monitoring and surveillance through handheld devices like cell phones to track the spread of diseases, epidemics, or pandemics; and (vi) accessing patient-related health information through electronic patient records [1].

mHealth has emerged as a means to improve access to high-quality healthcare services and information for a wider section of the population. It serves to connect the healthcare system with individuals by offering features such as appointment reminders, remote monitoring, virtual consultations, treatment assistance, health monitoring, disease surveillance, disease management, health analytics, as well as health education to overcome language and/or literacy barriers using easy-to-use icon-based interfaces, thereby closing the gap between the two [3]. Furthermore, mHealth has evolved into a practical platform for distributing health-related information and influencing health behaviors to prevent and self-manage diseases, partly due to its portability and widespread accessibility [4]. Over the past few years, there has been a significant surge in the utilization of mobile phones and wireless sensors for gathering and retrieving health data. The prevalent use of mHealth applications for activities like calorie counting, nutrition assessment, exercise logging, BMI (body mass index) calculation, and smoking cessation is noteworthy. However, these commendable endeavors are of relatively minor importance when compared to the immense potential of mHealth in advancing medical research and healthcare. Mobile devices offer a highly attractive, cost-effective, real-time means of evaluating various physiological factors, including disease, movement, photographs, behavior, social interactions, environmental toxins, and metabolites [5].

Silva et al. [6] emphasized that the deployment of mobile healthcare interventions, particularly in regions with scarce health resources, can provide healthcare access for a broader population at an economical cost, eliminating the need for individuals to personally visit healthcare facilities. Moreover, mHealth brings in the possibility of shifting tasks towards low-trained healthcare workers without compromising the quality of care; for example, by creating a medical unit within the referral hospital to supervise visits remotely. In developing countries, security issues [7] may also prevent medical professionals from physically travelling to certain areas. Hence, adopting a hybrid approach that combines or replaces physical visits with electronic connectivity through mobile technology can prove highly impactful. Additionally, numerous challenges exist in developing countries, such as political instability, limited access to resources, unequal availability of health resources and services, subpar health information management systems, corruption in healthcare services, insufficient oversight of health policy and planning, and a shortage of adequately trained professionals. Consequently, the health of the population becomes compromised [8–12].

A study by Borsari et al. [13] reported that mHealth systems facilitate the collection of clinical data and enable the creation of electronic patient records. The digital format increased healthcare providers' adherence to antenatal care recommendations, while the graphic interface facilitated women's engagement with and retention of the health education modules. The study recorded a 91.9% patient satisfaction rate.

Other studies in the context of antenatal care programs have measured pregnant women's behavior with the mHealth system "pregnancy and newborn diagnostic assessment (PANDA)". These studies reported that the PANDA app effectively enhanced pregnancy care. Respondents described the PANDA app as user-friendly with the potential for improving access to high-quality care for pregnant women in underserved areas, all while addressing language and literacy hurdles [14,15].

Aamir et al. [16] assessed the influences on the adoption of mobile health (mHealth) in resource-limited settings. They found that user-friendly design elements of the mHealth application and organizational backing for the use of mHealth technology were the primary drivers of mHealth adoption. Factors impeding adoption included inadequate ICT (information and communication technology) infrastructure and a lack of government guidelines. The research suggested that governmental support should focus on bolstering mHealth initiatives by improving ICT infrastructure, encouraging collaboration among healthcare providers, and implementing training programs for the public and caregivers.

1.1. mHealth Potential to Reduce Health Disparities

The rise in healthcare costs, the increase in the number of patients, and the lack of medical staff are only a few of the reasons why mHealth has become a viable solution for the problem of sustainability in healthcare delivery [17]. Racial and ethnic disparities in health status and quality of care are frequently caused by the decisions of physicians, healthcare algorithms with AI (artificial intelligence) bias [18], health systems administrators, and other staff members within healthcare systems. Some of these elements contribute to higher rates of discrimination against certain population groups, which, either directly or indirectly, increases healthcare disparities [19,20]. ICT has transformed healthcare services through electronic health records (EHRs), patient portals, telemedicine, and mHealth services, protecting patients from adverse outcomes and improving disease management in underserved populations [21]. Investing in the application of ICT has the potential to enhance the fair treatment of underserved groups by fostering better coordination of care, promoting adherence to guidelines, and reducing the need for repetitive testing [22]. However, there is a lack of studies on how investment in health ICT infrastructure can reduce inequality in the delivery of healthcare [19]. Researchers investigating this area have put forth three technological approaches aimed at diminishing healthcare disparities. Firstly, they suggest creating an electronic database containing demographic and social details of patients in underserved regions. This database would facilitate the formulation of strategies to enhance healthcare services for these populations. Secondly, there is an opportunity to enhance health monitoring by incorporating geographical and social determinants of health into clinical data and health outcomes, especially for region-specific populations. The third and most crucial advantage of technology is its capacity to enhance comprehension of the root causes of health inequalities and guide the development of targeted interventions [23]. A workshop was conducted in 2017 by the US National Institute on Minority Health and Health Disparities in conjunction with the National Science Foundation. The workshop aimed to examine the role of ICT in mitigating unequal access to healthcare services. The emphasis was placed on promoting health ICT solutions that are scalable, enduring, and successful, while underscoring the significance of community involvement, cultural competence, and patient-centered care as key elements in advancing health equity [24,25].

1.2. Theoretical Framework and Hypotheses Development

Considering the significance of technological and organizational factors in reducing health disparities and promoting mHealth and its outcomes, we based our study on the technology–organization–environment (TOE) framework [26], which was presented by Tornatzky and Fleischer in 1990. The TOE framework suggests that an organization's acceptance and adoption of a new technology are shaped by three main contexts: technological, organizational, and environmental. The technological context involves various internal and external factors that can improve organizational productivity. The organizational context encompasses the resources within the organization that support the technology adoption process. The environmental context pertains to the specific circumstances and conditions under which an organization functions (influenced by factors such as competition), the organization's ability to acquire external resources, and its interactions with the government [27]. In summary, the TOE framework offers a thorough organizational framework for understanding the adoption of technology. Moreover, researchers can utilize the TOE framework to explore the specific determinants (technological, organizational, and environmental) pertinent to their unique circumstances. Furthermore, empirical support for the TOE framework is evident in numerous studies that have examined the utilization of technology across various business models and economic sectors [28–37]. Therefore, we applied the TOE framework to formulate hypotheses about mHealth adoption behavior.

Our proposed framework (Figure 1) suggests that the adoption of mHealth is affected by the factors outlined in the TOE model, including relative advantage, compatibility, top management support, organizational readiness, external support, and government regulation.

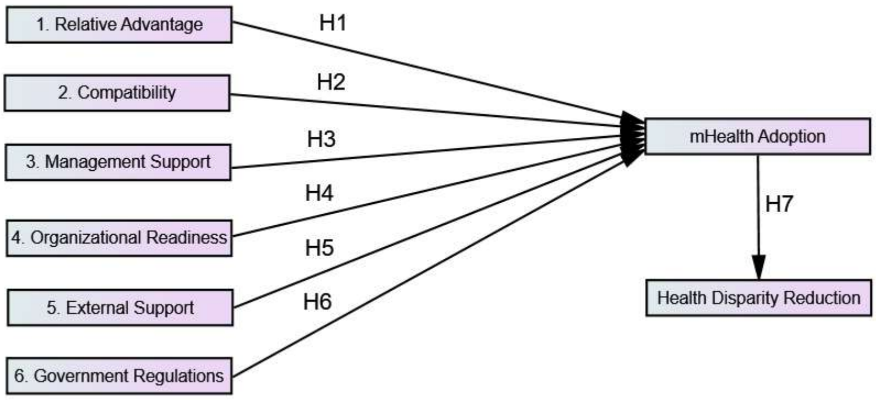

Figure 1. The authors' TOE-based conceptual framework and the development of hypotheses.

1.2.1. Technological Factors (TF)

The influence of costly technological advancements is a key factor in the overall expense of healthcare. Yet, there is insufficient evidence regarding how acquisition strategies, driven by hospitals' strategic decisions, impact the adoption of health innovations [38]. Successful implementation of any mHealth strategy necessitates a robust technological infrastructure. Factors such as acceptance and utilization of technology in developing countries, network coverage, power supply (particularly in remote or rural areas), among others, are crucial for the effective adoption of mHealth technologies. These technologies are key to facilitating real-time communication between patients and medical professionals, e.g., to monitor medication adherence and treatment compliance [39]. The monitoring and management of patients' blood pressure, for example, are facilitated through the utilization of mHealth adherence platforms, which incorporate features such as wireless data transfer, ECG (electrocardiogram), SMS (Short Message/Messaging Service), blood pressure monitoring apps, electronic reminder services, and electronic sensing devices. In developing countries, existing infrastructure challenges encompass cost, utilization and acceptance, network coverage, electricity availability, complexity, and compatibility. We have therefore formulated two hypotheses (H1 and H2, shown below) addressing technological aspects, namely relative advantage and compatibility. Relative advantage is described as the perceived improvement provided by the innovation compared with its predecessor, while compatibility is defined as the degree to which the innovation aligns with current values, experiences, and the needs of potential users [39–43].

H1. *The relative advantage of mHealth has a significant influence on mHealth adoption.*

H2. *The compatibility of technology has a statistically significant influence on mHealth adoption.*

1.2.2. Organizational Factors (OF)

Senior executives play a crucial role in fostering a favorable environment for integrating technology within an organization. This involves developing a comprehensive understanding of the benefits that technology adoption can bring to the organization [44]. With support from senior management, healthcare professionals can gain better clarity on their roles in delivering healthcare through mHealth [39]. Moreover, receiving backing from upper-level management helps to alleviate concerns among healthcare professionals about the implementation of mHealth solutions. The organization's commitment to training and support for the effective use of mHealth tools becomes apparent, instilling confidence. Additionally, the endorsement and utilization of mHealth by leaders significantly contribute to motivating individuals and, consequently, promoting broader implementation within the organization [45]. The inclination towards adoption is linked to the level of innovativeness shown by senior managers or leaders. Previous research has identified high-level management support and organizational readiness as crucial predictors of technology adoption [29,41,46,47]. Similarly, in the context of mHealth, a clinician's decision to adopt technology is influenced by organizational culture [48,49]. Based on this, we propose the following two hypotheses related to organizational factors:

H3. *Management support has a statistically significant influence on mHealth adoption.*

H4. *Organizational readiness has a statistically significant influence on mHealth adoption.*

1.2.3. Environmental Factors (EF)

The active engagement of clinicians throughout the creation, planning, and implementation phases can significantly impact their decision to adopt a technology. Physicians' adoption of mHealth technologies is influenced by several factors, encompassing policy and regulations related to legal protection, licensing, and credentialing, as well as considerations regarding costs and payment [50–52]. Environmental factors refer to challenges that organizations and individuals may encounter when they cross their external boundaries. Therefore, within our TOE-based framework, we have included external support and government regulation as environmental factors. External support may come from a vendor or third party to encourage individuals within an organization to innovate and adopt a new form of technology. Government regulations are defined as rules and regulations set by the government to promote technology adoption [53,54]. Based on the TOE model, we have formulated the following three hypotheses regarding environmental factors:

H5. *External support has a statistically significant influence on mHealth adoption.*

H6. *Government regulation has a statistically significant influence on mHealth adoption.*

H7. *mHealth adoption has a statistically significant influence on the reduction in health disparities.*

1.3. Study Objectives

The objectives were to (i) assess and authenticate the technology–organization–environment (TOE) theoretical framework, (ii) identify TOE factors impacting the adoption of mHealth technology among healthcare professionals (doctors and nurses), and (iii) gauge the impact of mHealth adoption on reducing health disparities in resource-limited settings in Pakistan.

2. Materials and Methods

2.1. Participants and Procedure

A cross-sectional survey was carried out at the six public and private hospitals in two districts (Lodhran and Multan) of Punjab, Pakistan. The population of the study comprised registered regular physicians and nurses working full-time in the participating hospitals. These hospitals are recognized and regularized by the Punjab Medical and Dental Council (PMDC), and the Pakistan Nursing and Midwifery Council (PNMC).

2.2. Research Instrument

After examining the existing literature related to the TOE theoretical framework [27,46,55–57] and mHealth [38,39,58] a questionnaire consisting of six sections was formulated. These sections assessed the study's settings, the participant's status in the healthcare facilities, infrastructure, enabling conditions, and the need for mHealth. The first section focused on demographic information, including gender, age, professional experience, profession (doctor or nurse), and working unit (emergency care, primary care, and medical or surgical units). The second section addressed technological factors with two sub-scales (relative advantage and compatibility) and eight statements. The third section covered organizational factors with two sub-scales (management support and organizational readiness) and seven statements. The fourth section explored environmental factors with two sub-scales (external support and government regulations) and seven statements. The fifth section included four statements on mHealth adoption, while the last section consisted of five statements on health disparity reduction. In total, the questionnaire comprised eight factors and thirty-one statements (as shown in Appendix A).

To ensure the questionnaire's quality, three professionals in information management, public health, and health communication conducted a pre-test, leading to suggested changes including statement rearrangements and rephrasing. A pilot test was performed on the first 20 responses to assess the validity of the questionnaire. However, we found no ambiguities that might lead to inaccurate data collection. The findings showed that the statements under each construct accurately assess the construct they aim to measure. The accuracy of data collection was assured by performing internal consistency checks within a respondent's answer, while each respondents' anonymity and confidentiality were also ensured. The questionnaire's reliability was assessed using Cronbach's alpha. The Cronbach's alpha scores were as follows: 0.865 for the four statements on management support (MS); 0.612 for the three items under organizational readiness (OG); 0.863 for the four items under relative advantage (RA); 0.895 for the four items loaded on compatibility (CP); 0.861 for the three statements on external support (ES); 0.763 for the statements on the government regulations construct (GR); 0.854 for the four statements about mHealth adoption (AD); and 0.85 for the five statements on health disparity (HD) reduction. The overall Cronbach's alpha value for the 31 statements across eight constructs was 0.85, indicating good reliability of the questionnaire.

2.3. Data Collection and Analysis Procedure

The survey for the study was distributed to participants using purposive sampling. A three-member research team, consisting of research students, voluntarily collected the data through personal visits to hospitals, distributing printed copies via surface mail, and sending a questionnaire link to participants' WhatsApp numbers and email IDs. In total, 500 questionnaires (both online and printed) were distributed, and after three follow-ups with two-week intervals 314 completed questionnaires were received, representing a response rate of 62.8%. All 314 questionnaires were deemed valid for data analysis. Data collection took place between March 2023 and May 2023.

We used the "statistical package for social sciences" (SPSS software v26) for the analysis of collected participants' data. Missing values in the dataset were addressed using expectation–maximization (EM) techniques, a widely accepted method for handling missing data. EM involves selecting random values for missing data points and estimating a second set of data based on those values.

Demographic information from the respondents was subjected to Chi-squared tests. For structural equation modeling (SEM), the analysis of moment structures (AMOS) was employed. SEM was utilized to estimate correlations between latent variables, assess the influence of exogenous variables on endogenous variables following the TOE theoretical framework pathways, and validate hypotheses. The significance level was set at <0.05.

2.4. Ethical Approval

The research commenced following the receipt of ethical approval from the Departmental Research Committee, Department of Information Management, the Islamia University of Bahawalpur, Pakistan, approval number: 4/DoIM, dated 16 December 2022. Informed consent was obtained from all questionnaire respondents.

3. Results

3.1. Demographic Information

Demographic information showed that of the 314 participants, the majority of males (117 or 78%) were doctors, and the majority of females (99 or 60.4%) were nurses (as shown in Table 1). We found a statistically significant gender distribution in two groups of doctors and nurses (χ^2 = 47.327, p = 0.000, phi's value = 0.388). Among the doctors, the majority (174 or 95.6%) were below 35 years of age, while the majority of nurses (94 or 71.2%) were within the same age group. Furthermore, there were only two (1.1%) doctors in the 36–50 age group, contrasting with 31 (23.5%) nurses in that category. This age-wise distribution of doctors and nurses showed statistical significance (χ^2 = 42.560, p = 0.000, Cramer's value = 0.368).

Table 1. Respondents' demographics.

	Doctors	**Nurses**	**χ^2 Value**	***p*-Value**	**Phi/ Cramer's V**
Gender					
Male	117 (78%)	33 (22%)	47.327	0.000	0.388
Female	65 (36.6%)	99 (60.4%)			
Total	182 (100%)	132 (100%)			
Age					
<35 years	174 (95.6%)	94 (71.2%)	42.560	0.000	0.368
36–50 years	2 (1.1%)	31 (23.5%)			
>50 years	6 (3.3%)	7 (5.3%)			
Total	182 (100%)	132 (100%)			
Experience					
<5 years	105 (57.7%)	88 (66.7%)	34.114	0.000	0.330
5–10 years	63 (34.6%)	38 (28.8%)			
11–15 Semester	8 (4.4%)	5 (3.8%)			
>15 years	6 (3.3%)	1 (0.8%)			
Total	182 (100%)	132 (100%)			
Setting					
Primary Healthcare	84 (46.1%)	27 (20.5%)	108.695	0.000	0.588
Medical/Surgical	56 (30.8%)	15 (11.4%)			
Intensive Care	11 (6%)	44 (33.3%)			
Emergency Unit	1 (0.5%)	35 (26.5%)			
Operating Unit	30 (16.5%)	11 (8.3%)			
Total	182 (100%)	132 (100%)			

A significant difference was also observed in the experience levels of doctors and nurses (χ^2 = 34.114, p = 0.000, Cramer's value = 0.330). Doctors tended to have more experience compared to nurses in our study cohort. The distribution of work settings between doctors and nurses also exhibited a significant difference (χ^2 = 108.695, p = 0.000, Cramer's value = 0.588). In our cohort, 44 (33.3%) nurses were working in intensive care compared to 11 (6%) doctors, while 35 (26.5%) nurses were in the emergency unit, contrasting with only one (0.5%) doctor in the same setting (Table 1).

3.2. Structural Equation Model

The eight-factor measurement model was estimated using structural equation modeling (SEM) based on 31 valid items.

3.2.1. Standardized Estimation of Regression Weights

Figure 2 displays the standardized values for SEM loadings and regression weights. The path coefficient values for latent variables range from β = 0.51 to β = 0.93, indicating robust loadings on the constructs. Within the construct 'relative advantage (RA)', four item loadings range from β = 0.75 to β = 0.82, and in 'compatibility (CP)', four item loadings range from β = 0.75 to β = 0.87, both demonstrating strong associations with the constructs. The 'management support (MS)' construct, consisting of four items, shows loadings ranging between β = 0.76 and β = 0.82. The latent variable 'organization readiness (OG)' is gauged using three observable variables, with loadings between β = 0.63 and β = 0.86, displaying a sound connection with the construct. The 'government regulations (GR)' latent variable, measured with four items, exhibits values between β = 0.57 and β = 0.75, signifying a credible association. The outcome variable 'adoption (AD)' displays loadings between β = 0.51 and β = 0.93, and the five items related to 'health disparity reduction (HD)' have loadings between 0.67 and 0.83, indicating strong associations with the constructs in Figure 2.

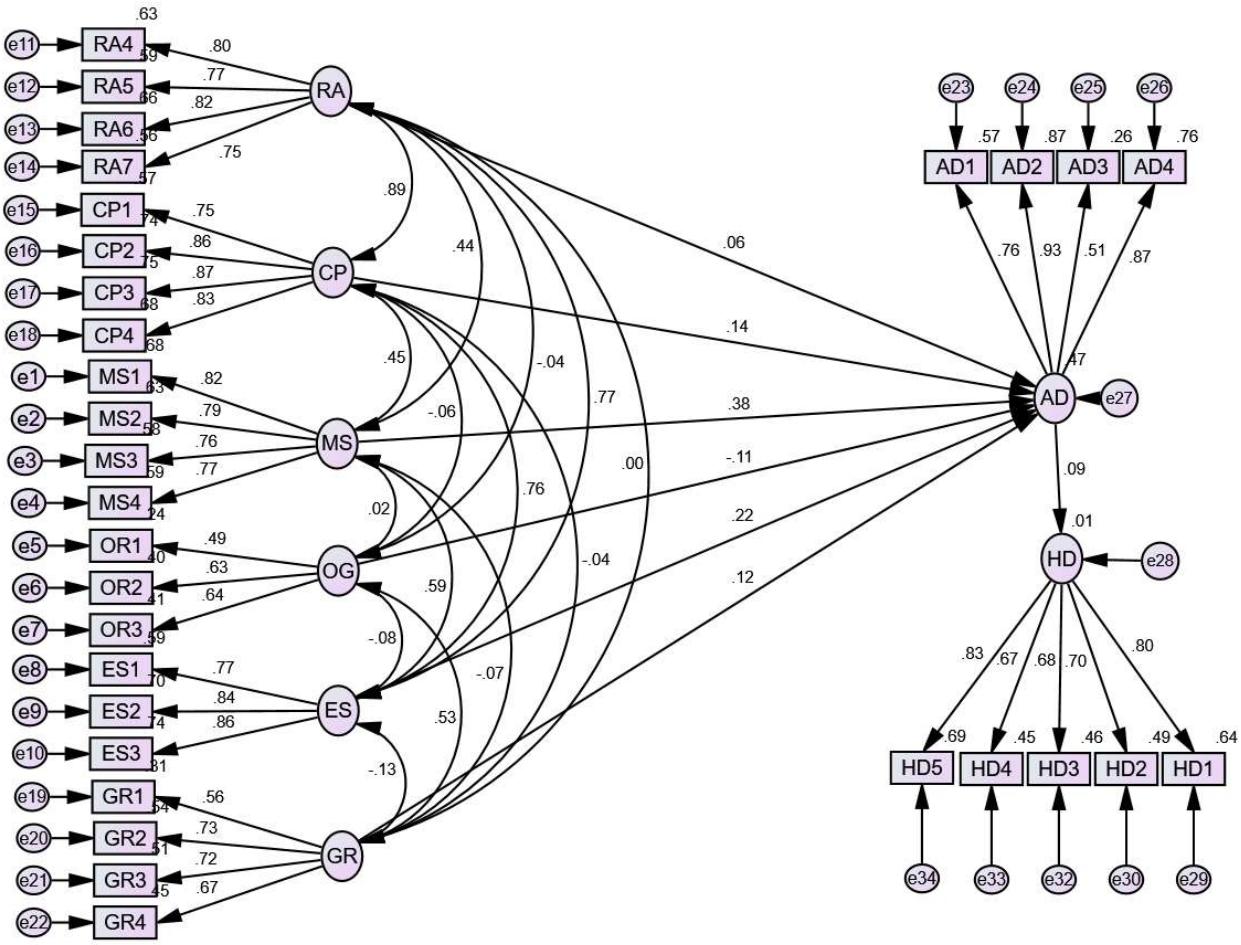

Figure 2. Structural equation model (SEM) estimates of the constructs. See Appendix A for detailed descriptions of relative advantage (RA), compatibility (CP), management support (MS), organizational readiness (OG), external support (ES), government regulations (GR), mHealth adoption (AD), and reduction in health disparity (HD).

Latent variables such as relative advantage (β = 0.053), compatibility (β = 0.154), management support (β = 0.376), organizational readiness (β = 0.041), external support (β = 0.220), and government regulation (β = 0.072) all positively impact mHealth adoption. However, the influence of these exogenous variables on the endogenous variable (mHealth adoption) is relatively weak. Conversely, mHealth adoption positively affects the reduction in health disparity (β = 0.090).

3.2.2. Standardized Estimation of Correlation among Latent Variables

The correlation values reveal that management support (MS) exhibits positive correlations with external support (ES) (β = 0.591), compatibility (CP) (β = 0.448), and relative advantage (RA) (β = 0.443). However, management support (MS) shows negative correlations with organizational readiness (OG) (β = −0.088) and government regulations (GR) (β = −0.068). Organizational readiness (OR) also demonstrates negative correlations with external support (ES) (β = −0.055), compatibility (CP) (β = −0.040), and government regulations (GR) (β = −0.034), while displaying a positive association with relative advantage (RA) (β = 0.010). External support (ES) is positively correlated with compatibility (CP) (β = 0.757) and relative advantage (RA) (β = 0.772) but exhibits a negative association with government regulations (GR) (β = −0.129). Compatibility (CP) is positively correlated with relative advantage (RA) (β = 0.892) but negatively correlated with government regulations (GR) (β = −0.036). Conversely, relative advantage is positively correlated with government regulations (GR) (β = 0.002).

3.2.3. Estimation of Covariances among Latent Variables

The results of covariance estimation among exogenous variables indicate a significant positive correlation of management support with external support (β = 0.370, CR = 7.396, $p < 0.05$), compatibility (β = 0.259, CR = 6.091, $p < 0.05$), and relative advantage (β = 0.244, CR = 5.943, $p < 0.05$). However, management support shows a non-significant negative correlation with organizational readiness (β = −0.036, CR = −1.299, $p > 0.05$) and government regulations (β = −0.041, CR = −0.989, $p > 0.05$). Conversely, organization readiness displays non-significant negative correlations with external support (β = −0.029, CR = −0.820, $p > 0.05$), compatibility (β = −0.019, CR = −0.611, $p > 0.05$), and government regulations (β = −0.017, CR = −0.476, $p > 0.05$). Additionally, relative advantage exhibits a positive but non-significant correlation with organizational readiness (β = 0.005, CR = 0.156, $p > 0.05$). External support demonstrates a significant positive correlation with compatibility (β = 0.533, CR = 8.982, $p < 0.05$) and relative advantage (β = 0.536, CR = 8.973, $p < 0.05$), while being negatively correlated with government regulations (β = −0.098, CR = −1.846, $p > 0.05$). Compatibility is significantly positively correlated with relative advantage (β = 0.572, CR = 9.570, $p < 0.05$), but non-significantly negatively correlated with government regulations (β = −0.025, CR = 0.047, $p > 0.05$). Lastly, government regulations show a positive but non-significant association with relative advantage (β = 0.001, CR = 0.025, $p > 0.05$).

3.2.4. Model Fit Indices

Model fit indices, including both absolute fit (χ^2, RMSEA) and additional fit (IFI, TLI, CFI) measures, are employed to assess the adequacy of the model fit. The goodness of fit indices suggest a favorable fit for the model, as evidenced by the following values: χ^2 = 2.050, DF = 0.412; $p = 0.000$; IFI = 0.920; and TLI = 0.909, CFI = 0.920, RMSEA = 0.058.

3.2.5. Standardized Estimation of Regression Weights and Validation of the Hypotheses

The validation of the hypotheses relies on key measures such as the standardized regression estimate, standard error (SE) for variable measurement, critical ratio (CR), and the significance among the factors. Regression analysis serves as an estimation tool enabling researchers to explore the relationship between two variables. As presented in Table 2, the results reveal that management support (β = 0.357, CR = 5.318, $p < 0.05$) and external support ($\beta = 0.166$, CR = 2.024, $p < 0.05$) exert a significant positive influence on mHealth adoption. However, relative advantage ($\beta = 0.045$, CR = 0.320, $p > 0.05$), compatibility ($\beta = 0.126$, CR = 1.018, $p > 0.05$), organizational readiness ($\beta = 0.047$, CR = 0.800, $p > 0.05$), and government regulations ($\beta = 0.057$, CR = 1.323, $p > 0.05$) demonstrate positive but non-significant influences on mHealth adoption. Furthermore, mHealth adoption exhibits a positive but statistically non-significant impact on health disparity reduction ($\beta = 0.109$, CR = 1.426, $p > 0.05$).

Table 2. Validation of the hypotheses. The significance level (α) set at $p = 0.05$, denoted by the star notation ('***'), indicates that the variable's value should not exceed the threshold value of 0.05.

	Factor		Factor	Estimate	S.E	C.R	*p*-Value	Result
H_1	Relative Advantage	–>	mHealth Adoption	0.045	0.141	0.320	0.749	Rejected
H_2	Compatibility	–>	mHealth Adoption	0.126	0.123	1.018	0.309	Rejected
H_3	Management support	–>	mHealth Adoption	0.357	0.067	5.318	***	Accepted
H_4	Organization readiness	–>	mHealth Adoption	0.047	0.059	0.800	0.424	Rejected
H_5	External support	–>	mHealth Adoption	0.166	0.082	2.024	***	Accepted
H_6	Government regulations	–>	mHealth Adoption	0.057	0.043	1.323	0.186	Rejected
H_7	mHealth adoption	–>	Health disparity reduction	0.109	0.076	1.426	0.154	Rejected

4. Discussion

Despite the potential benefits promised by mHealth in alleviating healthcare constraints and improving healthcare delivery, developing countries like Pakistan have not yet experienced the full extent of mobile health potential [59]. Our study used an eight-factor measurement model based on the technology–organization–environment (TOE) framework to explore mHealth adoption among healthcare professionals and its impact on reducing health disparities in underserved rural areas. While previous studies have applied the TOE model to predict mHealth adoption [38,39,45,58,60], this type of analysis is the first of its kind.

Building on the theoretical framework illustrated in Figure 1, we formulated seven hypotheses. For the two hypotheses regarding technological determinants, our findings revealed that relative advantage (RA) and compatibility (CP) positively influenced mHealth adoption (AD) but were statistically non-significant. This aligns with a study conducted in Kenya, which found no statistical significance of technological determinants on mHealth adoption [41], although the literature generally supports technological determinants as significant predictors of technology adoption [57,61,62]. Notably, our results validated the positive and significant influence of management support (MS), and organizational readiness (OG), on mHealth adoption, which is consistent with previous research studies emphasizing the role of organizational culture in clinicians' decisions to adopt technology [48,49]. This supports earlier findings that management support is a significant predictor of technology adoption [29,41,46,47].

Regarding environmental factors, our study confirmed that external support (ES) had a positive and statistically significant impact on mHealth adoption [63,64]. Additionally, our results suggested that government regulations (GR) positively influenced mHealth adoption (AD), aligning with a previous study emphasizing environmental determinants as significant predictors of mHealth adoption [38]. Moreover, our study found a positive but statistically non-significant impact of mHealth adoption (AD) on the reduction in health disparities (HD), which is comparable to previous studies [21,22,25].

In summary, the results of the structural equation modeling (SEM) analysis confirmed the validity of only two hypotheses, namely, the positive and statistically significant influence of management support (MS) and external support (ES) on mHealth adoption

(AD). Conversely, the impact of relative advantage (RA), compatibility (CP), organizational readiness (OR), and government regulations (GR) on mHealth adoption (AD), as well as the influence of mHealth adoption on reducing health disparities, were found to be positive but not statistically significant. Therefore, these five proposed hypotheses could not be validated due to the absence of statistical significance. Additionally, the SEM findings demonstrated acceptable goodness of fit indices, with $\chi^2 = 2.050$, df = 412; $p = 0.000$; IFI = 0.920; TLI = 0.909; CFI = 0.920; and RMSEA = 0.058, indicating that our proposed mHealth adoption model is deemed acceptable. This suggests that the model has the potential to contribute to mHealth adoption and the reduction in health disparities in low-resource settings.

On the whole, our study's findings are encouraging, indicating that all model constructs (RA, CP, MS, OG, ES, and GR) positively influence mHealth adoption (AD), consequently influencing the reduction in health disparities (HD). However, the strength of these influences (RA, CP, MS, OG, ES, and GR) on mHealth adoption (AD) ranges from 0.04 to 0.16, indicating a weak positive impact. Enhancing the strength of these influences may be achievable by contextualizing the findings within the participating institutions/settings and the basic characteristics of the study populations. For instance, Pakistan's telecom sector, similar to that of other developing countries, ranks low in terms of service quality for cellular users. Currently, it is ranked 79th out of 100 globally by the Inclusive Internet Index [65]. Therefore, the relative advantage (RA) or compatibility (CP) of mHealth adoption (AD) may have a weak influence as a result of inadequate technology infrastructure. Moreover, the poor impact of government regulations (GR) on mHealth adoption (AD) could be attributed to the absence of government policies and priorities directed towards mHealth solutions. The lack of a regulatory framework and inadequate government engagement are hindering emerging enterprises in Pakistan from introducing affordable and innovative healthcare initiatives, especially in the realm of mHealth applications.

Pakistan holds 45th position out of 100 in the Universal Health Coverage (UHC) rankings [66], a concerning placement given that it is the sixth most populous country globally, with a population exceeding 240 million in 2022 [67]. Despite recent increases in healthcare funding, Pakistan's health system continues to grapple with underfunding, resulting in an inadequate health infrastructure, scarcity of human resources, and fragile health information systems [68]. Primary healthcare providers in Pakistan encounter numerous challenges in accessing medical and patient information within this constrained environment. Barriers include the absence of a medical library and medical librarian, insufficient information technology infrastructure, outdated ICT equipment, limited information resources, and a lack of consultation between junior staff and more experienced senior professionals [69]. Furthermore, the health system faces regular disruptions and strains due to frequent health emergencies and natural disasters, such as floods, earthquakes, droughts, and outbreaks of diseases like measles and dengue. Additional challenges to the public health system include sluggish economic growth, security risks in certain regions, political instability, and subpar governance. In this scenario, our suggested mHealth model has the potential to significantly enhance medical outcomes, alleviate inefficiencies, broaden access, reduce costs, elevate quality, and personalize healthcare for patients. This approach also stands to benefit from the advantages offered by mHealth solutions [59].

Historically, foreign aid has been instrumental in advancing Pakistan's healthcare sector. As an illustration, the World Bank provides financial support under its National Health Support Program, aimed at enhancing the equitable and high-quality delivery of health services at the primary healthcare level, with the ultimate goal of achieving universal health coverage [70]. Based on our research findings, we recommend that health departments seek funding for mHealth by submitting relevant financial proposals to the World Bank and similar bodies. These proposals should outline plans for the utilization of mHealth to enhance health coverage and mitigate health disparities in low-resource settings within Pakistan. The funds secured can support the adoption of mobile health by providing resources for the development of mHealth apps and information technology infrastructure.

Additionally, organizing awareness sessions such as workshops and hands-on training sessions on digital health literacy can be facilitated through these funds. Inadequate digital health literacy affects a significant proportion of populations worldwide [71]. Improving digital health literacy skills, especially among young people (who make up a significant proportion of the population in developing nations), can help to tackle health inequalities and promote the health and well-being of both individuals and communities [72].

Informed by our study's findings, we believe that enhancing mHealth adoption is dependent upon emphasizing educational efforts, such as conducting practical training sessions for healthcare professionals to enhance their digital health literacy. Additionally, explaining the potential advantages of the utilization of mobile health solutions is crucial. Given the limited digital health literacy of many practitioners in low-resource settings, we recommend prioritizing simplicity and user-friendly interfaces in mHealth apps to cater to healthcare professionals with varying technological proficiency. Collaboration between healthcare providers, mobile app developers, and local communities is also essential for creating culturally relevant and accessible mHealth solutions. The development of mobile apps should be tailored to specific community health needs, incorporating local languages and cultural nuances for better resonance.

The study suggests that for mHealth adoption to be successful it needs to be endorsed by trusted figures, such as local community leaders, reputable influencers, and senior healthcare professionals. Moreover, our research emphasizes the need for a holistic approach that considers cultural norms, economic circumstances, and technological access factors in order to ensure the widespread adoption of mHealth within a community.

4.1. Study Limitations

Data were gathered through a survey method, relying on respondents' knowledge and self-reports. This approach introduces the potential for respondents' self-reported statements to deviate from the actual situation. To mitigate the questionnaire's limitations, it underwent pre-testing by two specialists in public health and health communication. The reliability of the questionnaire was assessed using Cronbach's alpha, resulting in a value of 0.85 for the 31 elements categorized into eight constructs, indicating its reliability.

Furthermore, we recognize the presence of the Dunning–Kruger effect (DKE), since the questionnaire relies on subjective self-reporting [73,74]. The DKE, a cognitive bias, manifests as the tendency to overestimate one's own abilities. This phenomenon, also known as "ignorance of one's own ignorance," occasionally leads to an inflated perception of knowledge or the ability to recognize something.

The study's lack of generalizability is acknowledged as a limitation due to variations in settings, demographic characteristics, technology infrastructure availability, and levels of digital health literacy among different populations. Therefore, caution is advised when extrapolating the findings to other populations or settings, such as tertiary or secondary healthcare populations.

4.2. Note to Readers

This paper is the second of a two-part large study on factors influencing mHealth adoption in low-resource settings. The first part, which tested additional hypotheses derived from the UTAUT (unified theory of acceptance and use of technology) model using a different set of survey questions administered to the same respondents as in this paper, is available at [17].

5. Conclusions

Our research affirms the applicability of the technology–organization–environment (TOE) framework in understanding the factors influencing the adoption of mHealth among healthcare professionals and its impact on reducing health disparities. The study indicates that both management support and external assistance play pivotal roles as primary predictors of mHealth adoption by healthcare professionals. The proposed mHealth adoption model from this study holds substantial potential in enhancing medical outcomes, minimizing inefficiencies and health disparities, broadening access, reducing costs, elevating quality, and customizing medicine for individual patients. Furthermore, the research suggests that a comprehensive approach, considering cultural, economic, technological, organizational, and environmental factors, is essential for the successful adoption of mHealth in low-resource settings.

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Data Availability Statement: The core data supporting the findings of this study are available within the article and its appendices. Further details can be obtained from the authors upon reasonable request.

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Appendix A

Table A1. Items under the eight constructs of the model.

Construct	Items	Measure	Sources
Relative Advantage (RA)	RA4	I think using mobile for healthcare improves patients' service and lowers the costs on healthcare provision.	[27,39]
	RA5	I think using mobile for healthcare brings in new service opportunities.	
	RA6	I think mHealth supports medical emergency response.	
	RA7	I think mHealth helps improve users' experience by offering better services.	
Compatibility (CP)	CP1	I think using mobile for healthcare is consistent with our practices.	[75]
	CP2	I think using mobile for healthcare fits our organizational culture.	
	CP3	I think that, overall, it is easy to incorporate mHealth into our organization.	
	CP4	I think mHealth apps are compatible with most of today's hand-held devices.	
Management Support (MS)	MS1	I think the adoption of mHealth for healthcare delivery is encouraged by our senior management.	[41]
	MS2	I think our senior management is willing to support mHealth adoption campaigns.	
	MS3	I think healthcare delivery through mHealth is a strategic endeavor that our top management places a high priority on.	
	MS4	I think our top management is enthusiastic about using mobile phone technologies in the healthcare industry.	

Table A1. *Cont.*

Construct	Items	Measure	Sources
Organizational Readiness (OG)	OG1	I think the hospital has the required resources to adopt mHealth solutions.	[56,57]
	OG2	The hospital/health department has organized workshops or trainings on ICT/computer proficiency in order to effectively adopt mHealth solutions for patient care.	
	OG3	I think the hospital aims to encourage mHealth solutions in the future.	
External Support (ES)	ES1	I think external funding agencies (such as Asian Development Bank, WHO, etc.) encourage adopting new health ICT (e.g., mHealth for quality patient care).	[76]
	ES2	I think health department can offer necessary training for using mHealth in healthcare	
	ES3	I think the health department can offer efficient technical assistance for the use of mHealth in healthcare	
Government Regulation (GR)	GR1	I think government regulations encourage adopting new information technology (e.g., mHealth for quality patient care).	[75]
	GR2	I think the government can provide the technical support, training, and funding to increase the usage of mHealth services	
	GR3	I think the government can support safeguarding security and privacy concerns while using the mHealth	
	GR4	I think government can be adaptable towards the regulations for advances in mHealth technologies	
mHealth Adoption (AD)	AD1	I think adopting an mHealth service will be a pleasant experience.	[17]
	AD2	I think mHealth can provide an opportunity to respond to patients more quickly.	
	AD3	I spend a lot of time using mHealth applications.	
	AD4	I think adopting mHealth can enable faster access to patient data.	
Health Disparity Reduction (HD)	HD1	I think mHealth is an effective solution for reducing health disparities.	[25]
	HD2	I am satisfied with the impact of mHealth adoption on improving healthcare access for marginalized communities.	
	HD3	mHealth initiatives can address the specific health needs of underserved populations.	
	HD4	I think mHealth has the potential to reduce health disparities in the healthcare setting/areas where I practice medicine.	
	HD5	I recommend mHealth solutions to colleagues for addressing health disparities.	

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