Exploring Factors Influencing the Adoption of Mobile Healthcare Technologies: Perspectives from Designers, Consultants and Users Preferences

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Design/methodology/approach

After a brief review of the literature, we identify the influential factors in the acceptance of smart technologies in healthcare systems and present a conceptual model in this regard. Next, we analyze the factors and variables and the extent of their impact by a structural equation modeling (SEM) approach. The statistical population of this study consists of 421 individuals including the developers, consultants, and users (i.e., patients) of mHealth apps. Data analysis was done on the statistical software SPSS v.26, while SEM was carried out using the partial least squares (PLS) method on the modeling software SmartPLS.

Purpose

Today, the use of smart technologies in healthcare systems is experiencing exponential growth, and the future of healthcare is seemingly closely intertwined with such technologies. Thus, any exploration of the factors that influence human health and healthcare systems inevitably touches upon the subject of new technologies. This study aims to design a conceptual model to investigate the elements that affect individuals' openness to accepting and using mobile healthcare applications (mHealth apps) and their reciprocal effects.

Findings

The results indicate that user, consultant, and developer preferences, have a positive and significant impact on time, quality of life, managing chronic conditions, and cooperation and these constructs (System Performance) finally have a positive and significant impact on the acceptance of mobile healthcare technologies.

Originality/value

This paper shows that mHealth apps can have a remarkable role in the prevention and treatment of medical conditions and it is strongly recommended that this technology be utilized in the studied region.

Keywords: Smart technologies, mobile health, mhealth, technology acceptance, healthcare systems, structural equation modeling.

1. Introduction

The term *smart health tech* is a combination of smart technologies and healthcare. Smart technologies, such as artificial intelligence (AI), have found widespread use in healthcare and medicine. Smart health tech makes it possible to monitor, record, and analyze medical data by various sensors and data storage devices, as well as communicating through virtual reality (VR), augmented reality (AR), and other media.

The emergence of smart tech in the healthcare system of countries is one of the factors that can contribute to the prevention and treatment of medical conditions. Since the overall health of a society strongly affects its growth and progress, developing applicable technologies for disease prevention and treatment is a clear necessity. Studies have shown that chronic health conditions negatively affect millions of Americans' life expectancy and quality of life Agnihothri (2018). With the ever-advancing world of today and consistent discovery of new technologies, humans and systems should gradually adapt to this new reality, as well, and try to attain a state of optimality. Healthcare systems are already transitioning toward new patterns and models and place enormous emphasis on disease prevention; therefore, elements such as availability and easy access to these technologies should be on top of the tech developers' priorities, Bettiga *et al*. (2020). It is expected that after the end of the COVID-19 pandemic, governments will make larger investments in smart tech, Kummitha (2020). In this regard, a key point requiring further research is the reasons why smart health tech is often rejected or avoided by potential users. In other words, there is an urgent need to better understand what characteristics and criteria make a mobile healthcare application (mHealth app) acceptable and useful to the average user.

The main objective of this study is to investigate the factors that affect the willingness to accept the use of smart tech in mobile-based healthcare systems by a structural equation modeling (SEM) approach. To this end, we identify the factors affecting users' acceptance of smart tech and design a conceptual model to measure the impact of the factors and their interrelationship. Section 2 presents a review of the literature. Sections 3 and 4 describe the research methodology and data analysis, respectively. And lastly, section 5 provides a brief conclusion along with a number of recommendations for future research.

2. Literature Review

Healthcare systems are moving toward new models and patterns that revolve around prevention. In this regard, there are emerging technologies whose purpose is to provide new tools to monitor individuals' vital signs and other health parameters. Bettiga *et al*. (2020) investigated the heart disease patients' openness to mHealth apps that provide preventive monitoring services. A partial least square structural equation modeling (PLS-SEM) approach was developed as part of the research to compute and analyze the findings. The authors found that the three parameters *perceived usefulness*, *perceived ease of use*, and *social influence* are decisive factors in the consumers' acceptance of the technology. The study presented an innovative set of perspectives with regards to designing and promoting mHealth apps as a way of boosting patients' health and provided valuable insights for medical doctors and researchers. Mobile health (mHealth) applications help reduce the burden of informal caregivers, Chiao *et al*. (2022) and also development of new technologies, particularly information technology (IT) has a great impact on the health care area and the quality-of-life style, Meigounpooy *et al*. (2014).

Mobile health applications (mHealth apps) offer enormous promise for illness monitoring and treatment to improve the provided medical care and promote health and wellbeing. mHealth apps undergo current developments, and they remain hot topics in COVID-19. These findings might be useful in determining future perspectives to improve infectious disease control and present innovative solutions for healthcare, El-Sherif *et al*. (2022). In addition, mHealth is being used to measure, predict, and prevent the full spectrum of injuries and mHealth for injury prevention holds promise, but further work is needed across the full spectrum of development and translation, Ranney *et al.* (2022). The global mHealth app market is rapidly expanding, especially since the COVID-19 pandemic and new relevant business models are required to be generated to satisfy the new emerging customers' expectations, Faghih *et al.* (2018). However, many of these mHealth apps have serious issues, as reported in their user reviews. Better understanding their key user concerns would help app developers improve their apps' quality and uptake. User satisfaction levels were compared amongst several mHealth app subcategories to investigate the impact of different aspects of mHealth apps on their ratings, Haggag *et al*. (2022). The patients' perceptions and healthcare employees' expectation, Mashhadiabdol *et al.* (2014) should be considered in mHealth app.

Healthcare workers' adoption of mHealth is critical to the success or failure of clinician based mHealth services in the developing world. mHealth adoption is affected or promoted by certain factors, some of which are peculiar to the developing world. Identifying these factors and evaluating them will help develop a valid and reliable measuring instrument for more successful prediction of mHealth adoption in the future, Addotey-Delove *et al*. (2022). Despite the high usage of mobile phones in daily life in developing countries like Bangladesh, the adoption and usage of mHealth services have been significantly low among the elderly population. Overall, the findings may contribute to shaping appropriate policies for designing and implementing mHealth services effectively for elderlies in developing countries, Palas *et al*. (2022). Appropriate designation of environment, resources, funds and improvement of functional indexes, Maleki *et al* (2014) & Sepehri *et al.* (2015) play a crucial rule in healthcare systems.

Chronic conditions incur considerable costs on healthcare systems and decrease the quality of millions of lives. Digital innovations, such as smartphones, can be employed to be part of an effective health monitoring plan. In an analytical study, Agnihothri *et al*. (2020) used the mHealth apps to monitor and manage chronic conditions such as diabetes and hypertension. Using a stochastic model, the authors considered various factors to evaluate the advantages of mHealth tech and by applying the Markov chain model, quantifying the evaluated advantages, and practitioners' intervention, modeled the progress of patients. Next, the interrelationship between the factors was outlined and the mHealth tech was found to be effective. It was observed that relying on mHealth apps instead of referring to hospitals gives patients a better chance of receiving intervention from service providers. Moreover, the authors concluded that successful interventions lead to better performance and more benefits for patients. Parati *et al*. (2018) demonstrated that remote blood pressure monitoring has a potentially key role in managing the condition of patients struggling with hypertension as it appears to improve the quality of care and ensures more effective prevention of the cardiovascular complications caused by hypertension. Lancioni *et al*. (2019) conducted a study on patients with advanced Alzheimer's disease and concluded that mHealth apps can help the patients maintain a considerable degree of independence. Similar studies on the impact of mHealth were published by Yousaf *et al*. (2019) and Yousaf *et al*. (2020) who showed that by providing simple interactive features, various combinations of care strategies, and support for the patients' relative caregivers, mHealth apps facilitate the use of healthcare facilities for Alzheimer's patients. Wang *et al*. (2018) conducted a comprehensive study on mental health-related mHealth apps. In spite of emphasizing the remarkable potential of these mobile applications in improving the management of mental disorders and their symptoms, the authors also pointed out that most of the available apps are not backed by strong clinical evidence. Therefore, given the number and release frequency of mHealth apps, there is a tangible need for more thorough research on the development and clinical testing of evidence-based apps.

Mobile health (mHealth) apps are increasingly being used to address mental and physical health concerns, and may be particularly beneficial for use among marginalized populations. The present findings provide important insight into the health-related symptom severity of individuals with distinct mHealth technology perceptions and motivational characteristics. These results may prove useful to consider in efforts aiming to improve the design of and increase engagement in mHealth interventions, Romano *et al*. (2022).

Obesity is considered an epidemic problem with an increasing number of individuals affected. The physical and psychological complaints associated with obesity point to the importance of implementing effective interventions. Innovative mHealth applications appear to be promising in helping provide a continuous and flexible support during the intervention, Fritsch *et al*. (2021).

Homecare, an increasingly pivotal component of healthcare systems, is another sector where mHealth apps have found resounding popularity. Homecare helps hospitals and retirement homes reduce their capacity and the costs of care. The basic function of mode of care is to ensure that those in need of daily medical service are properly monitored and cared for at a high standard, Demirbilek *et al.* (2019). Another application of mHealth apps is in telehealth or remote care. Nasir *et al.* (2018) integrated the work of a nurse and telehealth caregiver to monitor the physical or mental state of a patient, where the caregiver interacts with the patient and instructs the nurse in a video session from a remote location. The findings of Rajan *et al.* (2018) demonstrated that although in some cases the use of remote technologies may be detrimental to the patients' conditions, such developments ultimately improve the productivity of health workers and thereby enhance the society's wellbeing in the long term. The gathered data by apps can also help healthcare managers to use the simulation and optimization model, Kamali *et al.* (2018), Hatami-Marbini *et al.* (2022), Kamali *et al.* (2020), Shavandi *et al.* (2020) as well as the heuristic techniques, Sajadi *et al*. (2016), to make appropriate decisions in the healthcare system. These kinds of apps can also be sued in disasters such as earthquakes to save injured people by alerting and guiding them quickly to temporary medical centers, Mousavi (a) *et al.* (2021), Mousavi (b) *et al.* (2021) in a predesigned hierarchical network of medical centers for disasters, Mousavi (a) *et al.* (2022), Mousavi (b) *et al.* (2022), Mousavi(c) *et al.* (2022).

Promoting the integration of mHealth apps, internet of things (IoT), cloud computing, big data, and other technologies require increased investment in the information and knowledge on healthcare systems. Using big data analysis technologies and preventing disruptions in healthcare systems have made health services smart, as well and improved their quality. Zhou *et al. (*2020) attempted to predict the health trend of users through the grey prediction method and an adaptive clustering algorithm based on expanded data on IoT. The results confirmed that the algorithm proposed by the authors was quite efficient in predicting hypertension and other chronic conditions. Cardiovascular disease is one of the most common causes of death around the world. Yang *et al.* (2020) pointed out that in spite of remarkable recent developments in IoT technologies and the possibilities they provide to create smart health monitoring platforms, the application of such technologies to collect relevant data on heart disease at a large scare has remained very limited. The authors proposed an IoT-based model for cardiac monitoring and data collection and analysis to ensure early detection of abnormal heartbeat patterns that may signal existing or underlying heart conditions.

Emphasizing the positive impact of AI-based technologies on the quality of care and improvements in the wellbeing of disabled individuals, Amiribesheli and Bouchachia (2018) suggested that computational approaches and novel designs are able to improve the quality of dementia care by creating smart homes where persons with dementia (PwD) can live well and independently. A smart home is often equipped with a set of interconnected hardware and software that monitor, understand, and assist the activities of its residents. As human health is at risk more than any other time Mahabadi *et al*, (2015), the smart system implemented in such homes can detect risks and take proper action to ensure the safety, comfort, and satisfaction of smart home residents.

Finally, smart clothing and wearable technologies, primarily used for real-time monitoring of the human body, are becoming increasingly prevalent in health research. However, whether such technologies are welcomed by PwDs, or how long it takes them to accept smart clothing, is often unclear. According to Farina *et al.* (2019), the use of smart monitoring to observe the physical activities of PwDs has been both practical and acceptable, to the extent that most participants are able to wear smart clothing without problems for up to a month. Future research should investigate the needs of PwDs while wearing monitoring equipment with particular focus on ensuring that wearable technologies do not excessively intervene in the normal course of the wearers' lives.

According to Feroz *et al.* (2021), The review provides detailed information about the implementation of mobile phones at different levels of the healthcare system for improving young people SRH outcomes. This systematic review recommends that barriers to uptake mHealth interventions be adequately addressed to increase the potential use of mobile phones for improving access to SRH awareness and services.

Kabongo *et al.* (2021), in this study, we sought to uncover context, mechanisms, and outcome elements of various mHealth interventions based on implementation and evaluation studies to formulate theories or models explicating how mHealth interventions work (or not) both for health care providers and for pregnant women and mothers. Models developed in this study provide a detailed understanding of implementation and uptake of mHealth interventions and how and why they impact maternal and child health care in low- and middle-income countries.

An impressive body of literature has been produced on the subject of healthcare and technology, most of which confirming the vast development of smart health tech and its impact on healthcare systems. Table 1 summarizes some of the prominent studies in this field.

No.	Authors	Publ. year	Investigated factors		Objectives				Technology	Model	Research Methodology	Research Method Tools
			Acceptance	other	Prevention	Treatment	Quality improvement	Other				
1	Bettiga et al.	2020	✓	Willingness	✓	✓	✓	Requirements	Mobile	TAM	SEM	PLS-SEM
2	Avkiran	2018		-				-	-	PLS-SEM/ CB-SEM	SEM	GSCA
3	Agnihothri et al.	2020		Impact of relationships	✓		✓	Const reduction	Mobile	Markov chain	Stochastic	DTMC
4	Chen et al.	2018	✓	-	✓	✓	✓	-	Mobile	AST	Kano	Systematic
5	Qureshi et al.	2020	✓	-			✓	-	Mobile	Dynamic Predictive	cloud	Machine Learning
6	Parati et al.	2018		-	✓	✓	✓	-	Telehealth	HDM	BPT	DA
7	Guo et al.	2020		-	✓	✓	✓	-	Mobile	COX	Integrated Care	CRTs
8	Ko et al.	2019	✓	-		✓	✓	-	Mobile	-	MHT	Survey
9	Lancioni et al.	2019		-		✓	✓	Improving satisfaction	Mobile	SBO	PND	T test
10	Yousaf et al.	2019	✓	-		✓	✓	-	Mobile (apps)	-	Comprehensive	Systematic
11	Yousaf et al.	2020	✓	-		✓	✓	-	Mobile (apps)	AT	Comprehensive	Study Design
12	Knox et al.	2020	✓	Ease of access		✓	✓	-	Mobile (apps)	TAM	theoretically	PIS
13	Wang et al.	2018		-			✓	-	Mobile (apps)	-	Comprehensive	Systematic
14	Li et al.	2020	✓	Accessibility			✓	-	Mobile (apps)	-	MHA	Systematic
15	Yang and Lin	2019	✓	Social			✓	-	Mobile (apps)	TAM	theoretically	PLS
16	Demirbilek et al.	2019	✓	Planning	✓	✓	✓	More visits	HHC	SBO(HHNSP)	SBA	RG
17	Meigounpooy et al.	2014		-			✓	-	Mobile	Conceptual	SEM	SEM
18	Nasir et al.	2018		Planning			✓	Location	HHC/telehealth	ILPM	ILP	Fuzzy C
19	Nasir and Dang	2020		Planning			✓	Location	HHC	IDSM	MILP	Bender/ ROC
20	Chaieb et al.	2020		Scheduling			✓	-	HHC	HCSP	HOM	HDAG
21	Rajan et al.	2018	✓	Wellbeing	✓	✓	✓	Cost reduction	Telemedicine	Queuing model	Queuing	Operations
22	Zhou et al.	2020	✓	-	✓		✓	Control	IoT	GM(Simulation)	MapReduce	K-means Clustering
23	Yang et al.	2020		-	✓		✓	-	IoT	Network	Parallel computing	Analytical
24	Agnihothri et al.	2018		Behavior	✓		✓	Incentives	Mobile (apps)	IMCH(CCM)	EBM	RCTs
25	Amiribesheli and Bouchachia	2018	✓	Needs	✓		✓	-	Smart Home	CSM	AL	Fuzzy logic
26	Bavafa et al.	2018	✓	-	✓	✓	✓	-	E-visits	FEs	IV	Operations
27	Farina et al.	2019	✓	Feasibility study		✓	✓	-	Wearable	-	SWAT	QI
28	Hors-Fraile et al.	2018		Promotion		✓		Cost reduction	Smart System	-	HRS	MT
29	Chiu and Chen	2020		-			✓	-	Mobile	INLP	UCR	Fuzzy logic
30	Chen and Chiu	2020		-			✓	-	Mobile	INLP	UCR	BPN-RSM
31	Sarinho et al.	2018		Accessibility		✓	✓	Coverage of remote areas	EHR	Database	HIT	IT
32	Haggag et al.	2022	✓	-			✓	-	Mobile (apps)	-	Classification	Analytical
33	Feroz et al.	2021		Improve			✓	-	Mobile	-	Novel	Systematic
34	Chiao et al.	2022	✓	-			✓	-	Mobile (apps)	-		
35	El-Sherif et al.	2022		Improve	✓	✓	✓	Control	Mobile (apps)	-	Mapping	Analytical
36	Fritsch et al.	2021		-	✓	✓	✓	Control	Mobile	Curve		Analytical
37	Romano et al.	2022		-			✓	-	Mobile	-	Clustering	Analytical
38	Kabongo et al.	2021	✓	Impact			✓	-	Mobile	Explanatory	Realist	synthesis
39	Addotey-Delove et al.	2022	✓	Develop			✓	-	Mobile	SEM	Novel	HmAIM
40	Ranney et al.	2022		-	✓		✓	-	Mobile	Predictive		Analytical
41	Palas et al.	2022	✓	-			✓	-	Mobile	UTAUT2	empirical	Analytical

3. Research Methodology

In this study, we employ a mixed research methodology. In the first phase, 85 relevant studies were reviewed and a qualitative approach was applied to highlight the factors that affect the acceptance of smartphone-based healthcare technologies. A total of 23 influential factors were identified in 41 articles. In the second phase, interviews were conducted with the physicians of three Tehran hospitals (Farhikhtegan, Treata, and Nikan Gharb) and software developers from one of the largest IT companies in Iran. The aforementioned factors (illustrated in figure 1.) were approved by the doctors and developers interviewed in this study. In the third phase, a summary of the reviewed literature is presented in the form of a conceptual diagram in figure 1. Finally, in the fourth phase, the questionnaire is designed for the 23 factors and the research hypotheses are tested.

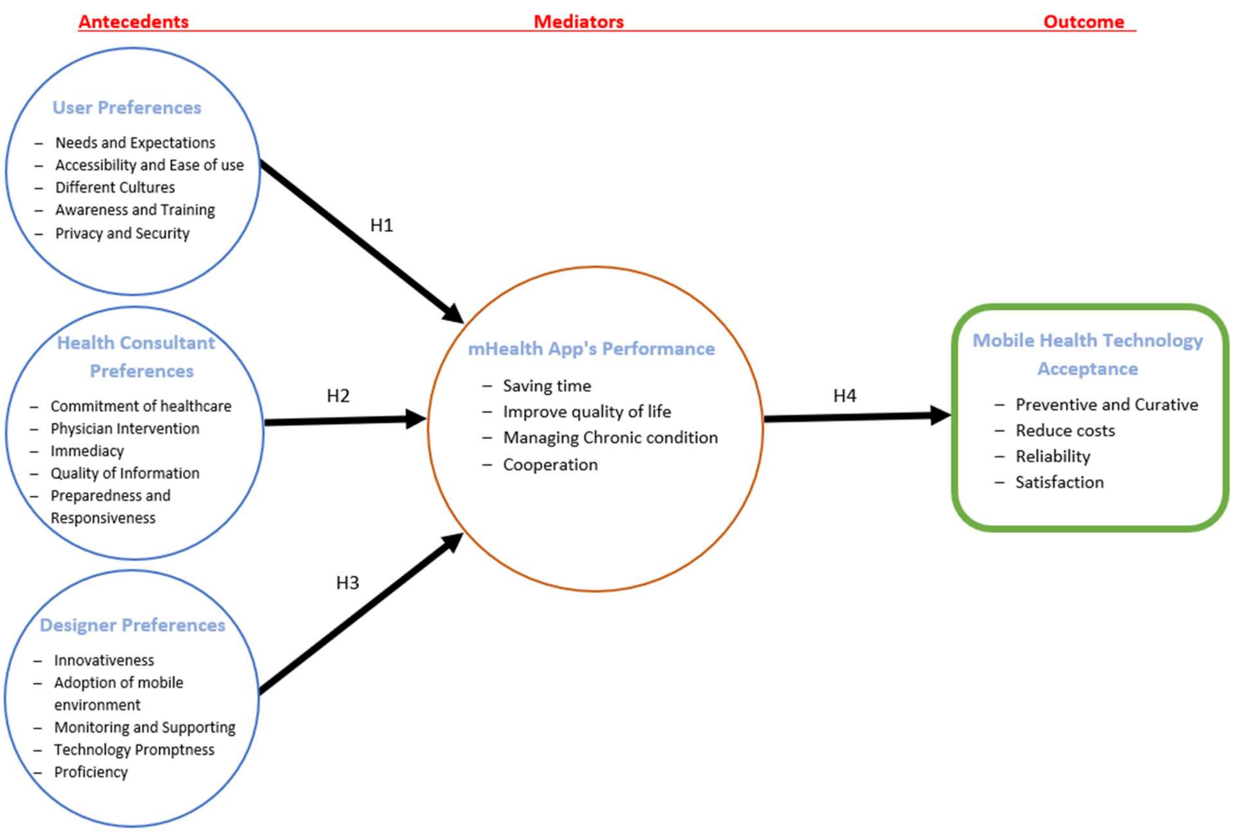

Figure 1 – Conceptual diagram of reviewed studies

Considering the conceptual diagram in figure 1, the research hypothesis are as follows:

H1: The preferences of users (patients who use the apps) affect the performance of mHealth apps.

H2: The preferences of consultants (physicians and other health professionals) affect the performance of mHealth apps.

H3: The preferences of designers (software and content developers) affect the performance of mHealth apps.

H4: The performance of mHealth apps affect the users' and consultants' acceptance of smartphone-based health technologies.

To test the hypotheses of the proposed model, the required data were collected by a five-point Likert scale questionnaire distributed to 421 users (incl. patients who use mHealth apps):321, consultants (incl. physicians and other health professionals):80, and designers (incl. software and content developers):20. Sampling was carried out based on statistical calculations, with the sample size determined by Cochran's formula. In the end, the factors, variables, and their impact were analyzed using SEM.

4. Data Analysis

In this section, we analyze the data collected from the questionnaires using the general SEM, a mix of measurement and structural models.

4.1. Evaluating the measurement model

Evaluating the model consists of examining the reliability and validity of the measurement model. There are two coefficients of reliability (internal consistency of observable variables in a test): Cronbach's alpha and composite reliability. The acceptable level for the model's internal consistency is 0.7. There are also two coefficients of validity: convergent validity and discriminant validity. The software SmartPLS provides indicators to measure the two coefficients for models.

4.2. Description of research variables

We use Likert's five-point response scale to measure performance and users' preferences. If the mean value of a variable is larger than its average score of 3, it means that the respondents consider the variable to be above-average. The opposite is also true. Moreover, if the skewness and kurtosis are within the boundaries of (–2, +2), the data are most likely distributed normally.

Table 2 – Descriptive indicators of variables

Variable	Descriptive indicators	No.	Min value	Max value	Mean	Standard deviation	Skewness	Kurtosis
Aspects of user preferences	Meeting needs and expectations	421	1.00	5.00	3.18	0.89	–0.034	–0.520
	Ease of access and availability	421	1.00	5.00	3.16	0.94	0.041	–0.421
	Considering different cultures	421	1.00	5.00	2.87	1.11	0.04	–0.681
	Awareness and education	421	1.00	5.00	2.35	0.95	0.599	–0.264
	Ensuring security and privacy	421	1.00	5.00	2.97	0.93	0.046	–0.306
	User preferences	421	1.27	5.00	2.91	0.78	0.383	–0.575
Aspects of consultant preferences	Effective intervention of physicians	421	1.00	5.00	2.95	1.02	0.002	–0.568
	Speed and timeliness	421	1.00	5.00	3.22	1.13	–0.177	–0.844

	Responsiveness and readiness	421	1.00	5.00	2.86	1.03	0.103	–0.475
	Relevant information	421	1.00	5.00	2.96	1.00	0.010	–0.385
	Commitment to patient's health	421	1.00	5.00	2.73	1.04	0.209	–0.389
	Consultant preferences	421	1.00	5.00	2.95	0.91	0.019	–0.615
Aspects of designer preferences	Innovation	421	1.00	5.00	2.87	1.07	0.026	–0.641
	Adaptability to new circumstances	421	1.00	5.00	3.42	1.13	–0.292	–0.716
	Supervision and support	421	1.00	5.00	2.62	1.07	0.179	–0.609
	Use of technologies	421	1.00	5.00	3.25	0.88	–0.007	–0.531
	Sufficient skill	421	1.00	5.00	2.95	0.97	0.037	–0.337
	Designer preferences	421	1.07	5.00	3.02	0.88	–0.035	–0.365
Aspects of performance	Efficiency	421	1.00	5.00	3.52	1.06	–0.254	–0.762
	Improving the quality of life	421	1.00	5.00	3.53	1.04	–0.166	–0.817
	Management of chronic conditions and diseases	421	1.00	5.00	3.41	1.13	–0.154	–0.828
	Interactivity	421	1.00	5.00	2.96	1.07	–0.261	–0.491
	Performance	421	1.25	5.00	3.35	0.96	–0.015	–0.781
Aspects of mHealth apps acceptance	Effective prevention and treatment	421	1.00	5.00	3.49	1.09	–0.210	–0.840
	Reducing costs	421	1.00	5.00	3.38	1.08	–0.209	–0.756
	Providing trust and assurance	421	1.00	5.00	2.98	1.08	0.094	–0.503
	Patient satisfaction	421	1.00	5.00	3.32	1.07	–0.216	–0.676
	mHealth acceptance	421	1.00	5.00	3.29	0.98	–0.267	–0.624

As table 2 indicates, the mean score of the indicator *meeting needs and expectations* is 3.18 with a deviation of 0.89. The mean score is larger than 3, indicating that the respondents consider the importance of this indicator to be above-average. Furthermore, this indicator has an insignificant skewness value of –0.034 and a kurtosis value of –0.520. Since both parameters are well within the boundaries of (–2, +2), they are highly likely to follow a normal distribution and can thereby be used for other descriptive indicators.

5. Inferential Analysis and Hypothesis Testing

In this section, we test the aforementioned research hypotheses by the Pearson correlation test and PLS-SEM on the statistical software SmartPLS. The Kolmogorov–Smirnov (K-S) test is applied to determine whether the data follow a normal distribution pattern. Thus, the statistical hypotheses are as follows:

H_0: The data are normal.

H_1: The data are not normal.

If the significance level of the test is larger than 0.05, H_1 is rejected and it can be concluded that the distribution of the data on a given variable is not significantly different from the normal state. The results of this test are detailed in Table 3 as follows:

Table 3 – Results of normality tests on research variables (n=421)

Variable	Kolmogorov–Smirnov test		Outcome
	Z-test	**P-value**	
User preferences	0.918	0.368	Normal
Consultant preferences	1.147	0.144	Normal
Designer preferences	0.569	0.902	Normal
Performance	1.227	0.099	Normal
mHealth acceptance	0.563	0.909	Normal

As can be observed, the K-S values obtained for the research variables have a larger significance level than 0.05; therefore, H_0 is not rejected and the data are normally distributed.

In addition, Pearson's test is applied to analyze the correlation between the research variables. The following hypotheses are defined for this test:

H_0: $r = 0$ ⇨ There is no relationship between the two variables.

H_1: $r \neq 0$ ⇨ There is a relationship between the two variables.

If significant correlation coefficients are between 0 and ±0.35, the correlation is considered weak and cannot be used in the prediction process. If the coefficient is within the boundaries of ±0.35 to ±0.65, the correlation is moderate, and if the coefficient is between ±0.65 and ±1, the correlation is strong and hence useful in individual and collective predictions. The sign of the correlation coefficient indicates the direction of the relationship. If the coefficient is a positive value, the relationship is direct and if negative, the relationship is inverse.

Table 4 – Pearson correlation coefficient between research variables (n=421)

Variable	User preferences	Consultant preferences	Designer preferences	Performance	mHealth acceptance
User preferences	1	----------	----------	----------	----------
Consultant preferences	0.763**	1	----------	----------	----------
Designer preferences	0.737**	0.766**	1	----------	----------
Performance	0.707**	0.738**	0.749**	1	----------
mHealth acceptance	0.611**	0.695**	0.624**	0.605**	1

** Significant at the 0.01 level (two-tailed test)

* Significant at the 0.05 level (two-tailed test)

It can be inferred from the data in Table 4 that there is a modest, positive, and significant correlation between the research variables at the 0.01 level. The strongest correlation ($r = 0.749$) is between *designer preferences* and *consultant preferences*, while the weakest ($r = 0.605$) is observed between *performance* and *mHealth acceptance*.

5.1. Examining research hypotheses

In order to examine the factors affecting the acceptance of smart tech and the extent of their influence, we apply a PLS-SEM approach on SmartPLS. The hypothetical model of the research was solved and analyzed also by SmartPLS according to the predicted variables and relationships. The analysis was carried out by estimating the path coefficients and the values of significance coefficients (t-value). The results are illustrated in the diagram below:

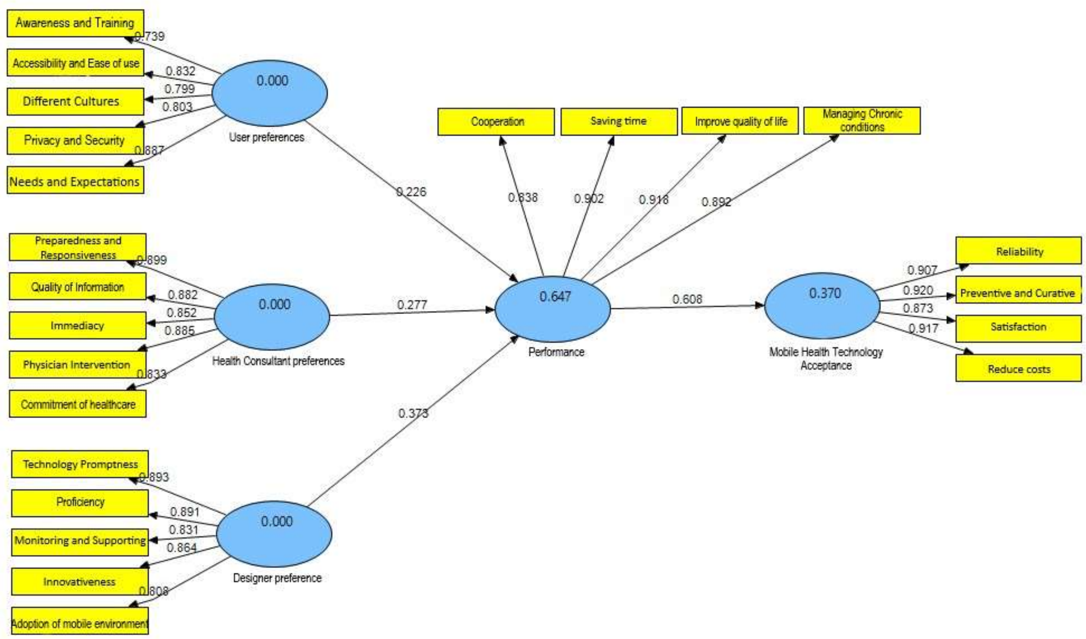

Figure 2 – Structural model of factors affecting mHealth acceptance in path coefficients mode

Figure 2 shows the path coefficients for the relationships between *user preferences*, *consultant preferences*, and *designer preferences* with *performance* and *mHealth acceptance*. As can be seen, the latent variables are not directly measurable and need to be measured based on two or three observable variables. The software presents the latent variables inside ovals and the observable variables – which are questionnaire items – inside rectangles.

The model displays path coefficients and factor loadings under conditions where standard coefficients are estimated. All the coefficients are positive values. A coefficient with a positive value indicates a direct relationship between the latent variables, while negative values suggest an inverse relationship. In the diagram above, the values written on paths indicate the path coefficients, the values inside ovals represent the determination coefficient (R^2) of the endogenous (dependent) variables, and the values on the arrows pointing to the observable variables represent the factor loadings. R^2 indicates what percentage of changes in the endogenous variables are caused by the exogenous variables. The values 0.19, 0.33, and 0.37 represent weak, moderate, and strong values for this indicator. It should be noted that all factor loadings are larger than 0.4.

The value of the determination coefficient for the variable *performance* is $R^2 = 0.647$. On this basis, the three variables *user preferences*, *consultant preferences*, and *designer preferences* have in total managed to predict 64.7% of the changes in *performance*. The value of the determination coefficient for the variable *mHealth acceptance* is $R^2 = 0.647$. Thus, *performance* has been able to predict 37% of the changes in *mHealth acceptance*.

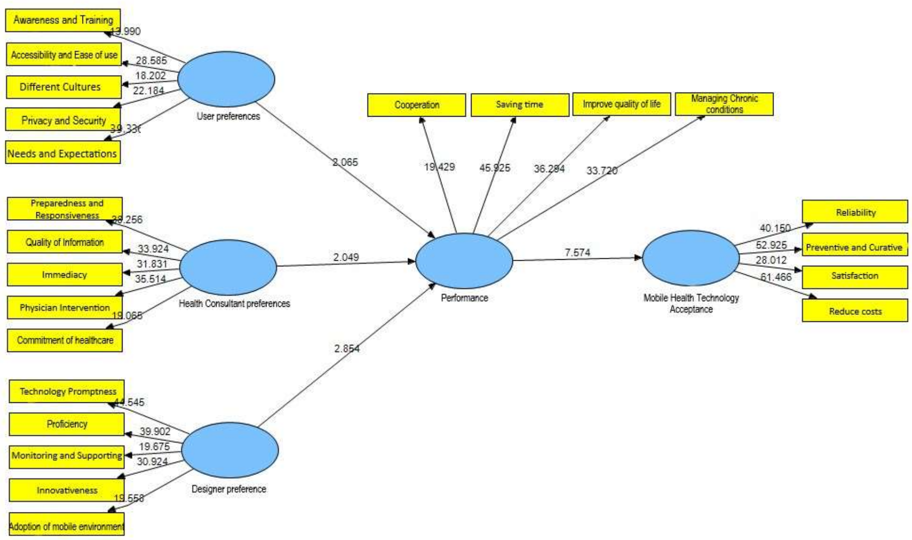

Figure 3 – Structural model of factors affecting mHealth acceptance in significance coefficients (t-value) mode

By examining the relationships between *user preferences*, *consultant preferences*, and *designer preferences* with *performance* and *mHealth acceptance* when the coefficients are significant (t-value), it is observed that the model tests all measurement and structural equations using t-statistic (see Figure 3). According to the model, if the absolute value of t-statistic for a path is larger than 1.96, the path coefficient and factor loading are significant at confidence level 95%.

- *Convergent validity*

Table 5 – Summary of reliability and convergent validity evaluation

Latent variable	Observable variable	Factor loading	T-value	Cronbach's alpha	Composite reliability	AVE	Acceptable level	Outcome
User preferences	Meeting needs and expectations	0.887	39.336	0.871	0.907	0.661	Factor loading > 0.4 AVE > 0.5	Reliability and convergent validity verified
	Ease of access and availability	0.832	28.585					
	Considering different cultures	0.799	18.202					
	Awareness and education	0.739	13.990					
	Ensuring security and privacy	0.803	22.184					
Consultant preferences	Effective intervention of physicians	0.885	35.514	0.920	0.940	0.758	Factor loading > 0.4 AVE > 0.5	Reliability and convergent validity verified
	Speed and timeliness	0.852	31.831					
	Responsiveness and readiness	0.899	38.256					
	Relevant information	0.882	33.924					
	Commitment to patient health	0.833	19.065					
Designer preferences	Innovation	0.864	30.924	0. 910	0.933	0.736	Factor loading > 0.4 AVE > 0.5	Reliability and convergent validity verified
	Adaptability to new circumstances	0.808	19.558					
	Supervision and support	0.831	19.675					
	Use of technologies	0.893	44.545					
	Sufficient skill	0.891	39.902					
Performance	Efficiency	0.902	45.925	0.910	0.937	0.789	Factor loading > 0.4 AVE > 0.5	Reliability and convergent validity verified
	Improving the quality of life	0.918	36.284					
	Management of chronic conditions and diseases	0.892	33.720					
	Interactivity	0.838	19.429					
mHealth acceptance	Effective prevention and treatment	0.920	52.925	0.926	0.947	0.819	Factor loading > 0.4 AVE > 0.5	Reliability and convergent validity verified
	Reducing costs	0.917	61.466					
	Providing trust and assurance	0.907	40.150					
	Patient satisfaction	0.917	28.012					

As table 5 shows, the values of the average variance extracted (AVE) for *user preferences* (0.661), *consultant preferences* (0.758), *designer preferences* (0.736), *performance* (0.789), and *mHealth acceptance* (0.819) are all larger than the acceptable level of 0.5. The factor loadings obtained in the process are also larger than 0.4 and thus significant. This confirms that the convergent validity of all variables is at an acceptable level. The values of Cronbach's alpha and composite reliability for all variables are estimated at larger than 0.7, indicating that the items applied in the questionnaire measure the same variable. In brief, all variables are adequately reliable.

- *Divergent (discriminant) validity at representative level (factor loading)*

We now use the cross-loadings table to examine divergent validity at the representative level. If the factor loading of any component on its own latent variable is larger than its factor loading on other latent variables by at least 0.1, the measurement model has divergent validity at the representative level.

Table 6 – Cross-loading of items to determine discriminant validity at cross-loading level

Item	**User preferences**	**Consultant preferences**	**Designer preferences**	**Performance**	**mHealth acceptance**
Meeting needs and expectations	0.887	0.691	0.605	0.669	0.589
Ease of access and availability	0.832	0.624	0.610	0.596	0.554
Considering different cultures	0.799	0.581	0.561	0.514	0.422
Awareness and education	0.739	0.543	0.594	0.524	0.379
Ensuring security and privacy	0.803	0.680	0.642	0.589	0.553
Effective intervention of physicians	0.686	0.885	0.683.	0.672	0.642
Speed and timeliness	0.619	0.852	0.609	0.612	0.613
Responsiveness and readiness	0.729	0.899	0.691	0.658	0.625
Relevant information	0.679	0.882	0.710	0.652	0.613
Commitment to patient's health	0.636	0.833	0.655	0.618	0.540
Innovation	0.622	0.639	0.864	0.636	0.521
Adaptability to new circumstances	0.574	0.619	0.808	0.573	0.498
Supervision and support	0.662	0.565	0.831	0.644	0.520
Use of technologies	0.671	0.703	0.893	0.722	0.601
Sufficient skill	0.636	0.680	0.891	0.644	0.548
Efficiency	0.633	0.669	0.661	0.902	0.586
Improving the quality of life	0.677	0.644	0.675	0.918	0.565
Management of chronic conditions and diseases	0.600	0.660	0.650	0.892	0.525
Interactivity	0.630	0.650	0.691	0.838	0.481
Effective prevention and treatment	0.540	0.6588	0.577	0.598	0.920
Reducing costs	0.548	0.624	0.544	0.558	0.917
Providing trust and assurance		0.665	0.626	0.550	0.907
Patient satisfaction	0.533	0.570	0.525	0.487	**0.917**

Table 6 shows that the factor loading of each item on its respective variable is larger than its factor loading on other factors by at least 0.1. Therefore, the measurement model has divergent validity at the level of its representatives.

- *Divergent (discriminant) validity at construct level (factor loading)*

In order to analyze divergent validity at the construct level, the square root of the AVE of each construct is compared with the correlation coefficients between the constructs. To do so, a matrix should be formed where the values on its main diagonal are the square roots of each construct's AVE and the values above and under the main diagonal are the correlation coefficients between each construct and the others. In case the correlation coefficients of a construct with the other constructs are less than the square root of that construct's AVE, its divergent validity is verified.

Table 7 – Comparison matrix of square root of AVE and correlation coefficients of variables

Variable	User preferences	Consultant preferences	Designer preferences	Performance	mHealth acceptance
User preferences	**0.813**	-----	-----	-----	-----
Consultant preferences	0.770	**0.871**	-----	-----	-----
Designer preferences	0.739	0.770	**0.858**	-----	-----
Performance	0.715	0.738	0.754	**0.888**	-----
mHealth acceptance	0.621	0.697	0.629	0.608	**0.905**

As can be seen in table 7, the correlation coefficients of each variable with the other variables are less than the square root of the AVE located on the main diagonal of the matrix. This indicates that the divergent validity of the variables is acceptable.

5.2. Examining general model and its fitness

In PLS-SEM, unlike covariance-based methods such as AMOS and LISREL, there is no single component to evaluate the entire model. However, there is an index known as goodness-of-fit (GoF) introduced by Tenenhaus *et al*. (2005) which is relied upon as a criterion to test the overall performance of models. The value of GoF is between 0 and 1. According to Wetzels *et al*. (2009), the values 0.01, 0.25, and 0.36 represent poor, moderate, and strong GoF, respectively. GoF is obtained as follows:

(1) $\text{GoF} = \sqrt{\overline{communality} \times \overline{R^2}}$

(2) GoF = 0.619

Where $\overline{R^2}$ is the average of determination coefficients and $\overline{communality}$ the average of communality values. The index for our model is calculated at 0.619 which indicates strong GoF in the general model. Based on the test results, it can be concluded that the model has good fitness.

Table 8 - Predictive relevance of the model

Variable	Q^2
User preferences	0.661
Consultant preferences	0.758
Designer preferences	0.736
Performance	0.778
mHealth acceptance	0.814

The predictive relevance index is evaluated by Stone-Geisser's Q^2 measure. As table 8 shows, the values of Q^2 are larger than zero, indicating that the observable values are reproduced well and that the model is able to make good predictions. 0.02, 0.15, and 0.35 are considered poor, moderate, and strong Q^2 values, respectively. Since all the values obtained for this model are both positive and larger than 0.35, it can be said that the structural model has adequate quality. The results of the structural part of the model i.e. the measures calculated for the model's paths, including the standardized path coefficient (β) and t-values at an error rate of 5% are presented in table 9.

Table 9 – Results of structural part of the model

			Path coefficient	t-value	SE	Critical t-value	f^2	R^2	Relationship direction	Test result
User preferences	→	**Performance**	0.226	2.065	0.109	1.96	0.048	0.647	Positive	Verified
Consultant preferences	→	**Performance**	0.277	2.049	0.135	1.96	0.068		Positive	Verified
Designer preferences	→	**Performance**	0.373	2.854	0.131	1.96	0.139		Positive	Verified
Performance	→	**mHealth acceptance**	0.608	7.574	0.080	1.96		0.370	Positive	Verified

We use Cohen's f^2, a standardized measure of effect size, to determine the intensity of the relationship between the model's latent variables. It measures the effect size of an exogenous variable on an endogenous variable in structural equations. According to Cohen, the values 0.02, 0.15, and 0.35 represent poor, moderate, and strong f^2, respectively. The estimated f^2 values, as detailed in table 8, indicate that the paths have adequate effect sizes. Based on the data in table 8, path coefficients, and t-statistics, it can be said that:

❖ Bettiga *et al*. (2020) also explored factors including *needs and expectations*, *availability and ease of access*, *considering different cultures*, *awareness and education*, and *ensuring security and privacy* using SEM. In the present study, we classified these five factors, which have a direct relationship with the dependent variable *mHealth acceptance*, under *user preferences.* The t-value ($t = 2.065$, $p < 0.05$) obtained for the path between the two variables *user preferences* and *performance* is larger and more significant than the critical t-value (1.96). Therefore, it can be concluded at a 95% confidence level that the variable *user preferences* has a positive and significant relationship *($\beta = 0.226$)* with *mHealth acceptance*.

❖ As for *consultant preferences*, we used the parameters explored by Chen *et al.* (2018) in a macro model and by Agnihothri (2018) in a systematic review. These included *effective intervention of physicians, speed and timeliness, responsiveness and readiness, relevant information,* and *commitment to patient's health,* as the influential factors in this study. The t-value ($t = 2.049$, $p < 0.05$) obtained for the path between *consultant preferences* and *performance* is larger and more significant than the critical t-value (1.96). Thus, it can be said at a 95% confidence level that the variable *user preferences* has a positive and significant relationship *($\beta = 0.277$)* with *mHealth acceptance*.

❖ In the case of *designer preferences*, we made use of the factors investigated by Chen *et al.* (2018) and Bettiga *et al*. (2020) which have a positive relationship with the acceptance of smartphone-based technologies. The factors included *innovation*, *adaptability to new circumstances*, *supervision and support*, *use of technologies*, and *sufficient skill*. The t-value ($t = 2.854$, $p < 0.05$) obtained for the path between *designer preferences* and *performance* is larger and more significant than the critical t-value (1.96). Hence, it can be stated at a 95% confidence level that the variable *designer preferences* has a positive and significant relationship *($\beta = 0.277$)* with *mHealth acceptance*.

❖ The mediating variable *performance* has a direct role in determining the variable *mHealth acceptance* through the independent variables *user preferences*, *consultant preferences*, and *designer preferences*. To be specific, performance consists of the four factors *efficiency*, *improving the quality of life*, *management of chronic conditions and diseases*, and *interactivity*. The t-value ($t = 2.854$, $p < 0.05$) calculated for the path between the two variables *performance* and mHealth acceptance is larger and more significant than the critical t-value (1.96). Consequently, it can be concluded at a 95% confidence level that the variable *performance* has a positive and significant relationship *($\beta = 0.608$)* with *mHealth acceptance*.

6. Conclusion

In this research, we investigated the factors that affect the acceptance of smart mobile-based healthcare (mHealth) technologies among various groups of individuals through a comprehensive review of the existing literature. A total of 23 factors were identified, all of which found to have a significant impact, and classified under five sets of variables: *user preferences*, *consultant preferences*, *designer preferences*, mHealth app's *performance*, and *mHealth acceptance*. Moreover, users, consultants, and designers preferences and the *mHealth* app's performance appeared to have a positive and significant impact on mHealth acceptance. For instance, the factors *meeting expectations*, *ease of access, efficiency, sufficient skill*, *circumstances supervision and support, effective intervention of physicians, timeliness, relevant information, responsiveness, improving life quality,* and *management of chronic conditions* had a major role in the model designed in this study for individuals' willingness to accept mHealth apps. Furthermore, *reducing costs*, *effective prevention and treatment*, *security and privacy*, and *patient satisfaction* had a considerable role in measuring the variables. The review of the literature showed that no comprehensive model had been developed in prior studies to cover all the factors involved in an integrated manner. In the present research, we made a deliberate effort to produce a comprehensive model that would encompass all the factors that affect the acceptance of mHealth apps. In future research, other smart technologies in this sector can be explored and modeled. Alternatively, examining the mHealth factors identified in this study through other available methods and employing different modeling approaches may be promising areas for research in the future.

6.1. Discussion and implications

Mobile health, or mHealth, is a rapidly growing field that has the potential to revolutionize healthcare delivery. The use of mobile devices such as smartphones and tablets to support healthcare services has the potential to improve access to care, increase patient engagement, reduce healthcare costs, and improve health outcomes. However, there are also concerns about privacy and security, as well as regulatory challenges that must be addressed to ensure that mHealth technologies are used safely and effectively. One of the most significant implications of mHealth is improved access to healthcare services, especially in remote and underserved areas. Mobile technologies can be used to provide telemedicine services, enabling patients to receive medical consultations and treatment remotely. This is particularly important for patients who live in areas where traditional healthcare services may be limited or unavailable. In addition, mHealth tools can be used to provide health information and education to patients, enabling them to take a more active role in their own healthcare. Another key implication of mHealth is increased patient engagement. By providing patients with access to health information, tracking their health data, and enabling them to communicate with their healthcare providers, mHealth tools can help patients become more engaged in their own healthcare. This can lead to better health outcomes and reduced healthcare costs, as patients are more likely to adhere to treatment plans and make lifestyle changes that can improve their health. Cost savings are another important implication of mHealth. By enabling remote monitoring and management of chronic diseases, reducing hospital readmissions, and improving medication adherence, mHealth has the potential to reduce healthcare costs significantly. This is particularly important given the rising cost of healthcare and the increasing prevalence of chronic diseases such as diabetes and heart disease. However, there are also concerns about privacy and security when it comes to mHealth. The use of mobile devices for healthcare purposes raises concerns about the privacy and security of patient health information. It is important to ensure that appropriate safeguards are in place to protect patient privacy and prevent data breaches. This includes implementing strong security protocols, training healthcare providers on best practices for data security, and ensuring that patients are informed about how their data will be used and protected. Finally, regulatory challenges must also be addressed to ensure that mHealth technologies are used safely and effectively. mHealth technologies are subject to regulatory oversight, which can create challenges for developers and healthcare providers seeking to implement these technologies. It is important to navigate these regulations carefully to ensure compliance with relevant laws and regulations.

The model developed in this study can help create and/or improve smartphone applications and websites dedicated to patient-physician communication and provide fresh insights for healthcare decision-makers, executives, consultants, physicians, and software developers. Although numerous technologies have been developed in the health sector with a diverse set of functions and applications, the present study was solely concerned with mHealth technologies.

6.2. Limitations and Future research

One limitation of this study could be the sample selection bias, as it only includes individuals who are developers, consultants, and users of mHealth apps. This may not be representative of the general population or other healthcare providers who may have different attitudes toward the use of smart technologies in healthcare. Additionally, the study focuses solely on mHealth apps and does not consider other forms of smart technologies in healthcare systems. Another limitation could be the reliance on self-reported data, which may be subject to social desirability bias and may not accurately reflect the actual behavior of individuals. Furthermore, the study does not address potential ethical and privacy concerns associated with the use of smart technologies in healthcare systems. Finally, the study was conducted in a specific region, which may limit the generalizability of the findings to other regions or countries.

This article specifically focuses on mobile health applications, it would be interesting to investigate the impact of smart technologies in healthcare more broadly. This could include exploring the impact of smart devices, wearables, and other healthcare technology on patient outcomes, provider workflows, and healthcare costs. This study also highlights the importance of users, consultants, and developers preferences in technology acceptance. However, it does not delve into the specific design factors that contribute to these preferences. A future study could explore the impact of user interface design on technology acceptance and identify best practices for designing healthcare technology that is user-friendly and effective.Finally, this study was conducted in a specific region and does not explore potential cultural differences in technology acceptance. A future study could investigate how attitudes towards healthcare technology vary across cultures and explore potential strategies for increasing technology acceptance in different cultural contexts.

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