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RESEARCH PAPER

An Empirical Evaluation of Technology Acceptance Model in Mobile Devices in Healthcare Industry

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ABSTRACT

Digital technology is spreading overall industry with a rapid growth, especially in the healthcare industry. Researcher are globally working on different models of technology acceptance but from the initial day technology acceptance was a dilemma for the scientists. This study aims to investigate how patient trust on the healthcare related mobile applications will leads towards their usage and what is the role of the technology acceptance model in this prospective. Primary data was collected from the 345 different patients of Karachi city who are the users of different mobile healthcare applications by a closed ended questionnaire through judgmental sampling. The gathered data was analyzed by using a Partial Least Square approach with SmartPLS software. The result of this study shows that trust is one of the key factors which promotes the usage of the healthcare mobile applications through the technology acceptance model among the patients of Karachi city. Results also shows that the usage of the healthcare related applications are mainly based on how much patients trust the application. More trust in the result and more usage of the application devices. Furthermore it is recommended to the healthcare sector to increase their investment in the area of artificial intelligence to enhance it accordingly.

KEYWORDS Artificial Intelligence, TAM Model, Mobile Devices, Healthcare Sector

Introduction

In present ages, the inclusion of digital technology through businesses has converted active standards, with the health care sector being no exception. The presence and speedy growth of healthcare-related mobile applications (mental Health apps) have introduced a transformative shift in how healthcare services are retrieved, managed, and delivered, emphasizing patient-centric care and real-time health monitoring (Alalwan et al., 2017). In the mental Health domain, trust operates as both a direct antecedent to usage intention and an indirect influencer through its impact on perceived usefulness and ease of use (Misra et al., 2025). demonstrated that trust in app developers, data handling practices, and platform security directly increased PU and PEOU, thereby reinforcing the overall intention to use mHealth apps (Kumar et al., 2024). Furthermore, the significance of trust is amplified in healthcare settings due to the vulnerability of users, the critical nature of the services, and the reliance on accurate, timely information for health-related decision-making (Wang & Qi, 2021). Trust, therefore, becomes not only a psychological factor but a pragmatic requirement for technology adoption in healthcare (Shirazi & Mohammadi, 2019). Several scholars have proposed extensions to the TAM, such as TAM2 and the Unified Theory of Acceptance and Use of Technology (UTAUT), to account for contextual variables like trust, perceived risk, and social influence (Venkatesh et al., 2003). According to these models the technological attributes like interface design, the system reliability, and functionality are very necessary for the trust acts as a mediating or moderating variable that can amplify or diminish the effect of PU and PEOU (Kim & Park, 2012). In some cases patients thinks that some of the applications are highly beneficial to them but they don’t use these application due to security threats (O'Gorman et al., 2016) . as we know the experts those who are involve in the development of the healthcare related applications don't only focus on the benefits of the applications that how much this is beneficial to the patients but they mainly focus how the security and trust measured are incorporated (Amanda & Layman, 2022).

Literature review

It was also found that the trust level among the patients for the same application is not same for all the patients. In this context demographic variables highly impact the scenario specially age of the patients and other related demographic factors (X. Zhang, Guo, et al., 2014). Elderly users, for example, may require additional assurances regarding the credibility of digital platforms, as their perceived risk often outweighs their technological enthusiasm (Hwang et al., 2025). Additionally, cultural context plays a significant role in shaping trust perceptions and technology acceptance behaviors, as collectivist societies may rely more heavily on peer recommendations and institutional reputation compared to individualist cultures (Luo et al., 2010). In examining the role of trust in TAM within the healthcare mobile app context, researchers have also highlighted the importance of experiential and affective trust, which derives from personal interactions with the technology rather than institutional factors alone (Gefen et al., 2003). This highlights the requirement of user-friendly proposal, innate triangulation, and optimistic user experience in humanizing trust and thereby endorsing implementation. Additionally, post-adoption trust, which evolves through continuous interaction and satisfaction, is critical for long-term usage and engagement (Nikou & Economides, 2017). The cyclical relationship between trust and usage indicates that positive user experience reinforces trust, which in turn sustains engagement—a dynamic often encapsulated in trust-based technology acceptance models (Jensen et al., 2015). Furthermore, as artificial intelligence and machine learning capabilities become united into mental Health apps, the need for algorithmic clearness and explainability becomes essential in maintaining user trust (Izumi, 2025). Lack of clearness in how health recommendations or diagnostics are shaped may deter clients, specifically when serious health findings are at risk (Longoni et al., 2019). Thus, future repetitions of TAM in health care technology should adapt forward-moving trust dimensions including algorithmic trust, ethical AI, and identified data supremacy (J. A. Zhang et al., 2020). Consequently, mixing constructs from behavioral theories such as the Theory of Planned Behavior (TPB) and Protection Motivation Theory (PMT) alongside TAM can offer a more complete thoughtful of mental Health adoption (X. Zhang, Onita, et al., 2014). For example, PMT clarifies that perceived severity and susceptibility effect conduct together with trust in protective machinery (e.g., mental Health apps for disease tracking), making it a precious addition to TAM. Additionally, empirical evidence from longitudinal studies has demonstrated that trust-enhancing features such as privacy notices, feedback mechanisms, and user control significantly increase sustained usage of health apps (Hengst et al., 2023). As the digital health site continues to evolve, with novelties such as remote patient monitoring, wearable integration, and telemedicine, the authoritative to understand how trust impacts technology reception becomes even more dangerous (Kato et al., 2020). Thus, academic and industry stakeholders must continue to refine theoretical models like TAM to include comprehensive trust metrics, ensuring a holistic understanding of adoption behavior in mental Health settings (Jarrahi, 2018). In summary, while the Technology Acceptance Model remains a foundational framework for examining the determinants of healthcare technology , incorporating trust into its structure is indispensable for accurately predicting and enhancing patient engagement with mobile health applications (Jamil et al., 2025). By recognizing trust as a central, dynamic, and context-sensitive factor, researchers and practitioners can better design, evaluate, and implement digital health solutions that are not only functional and user-friendly but also ethically responsible and emotionally reassuring to the end-users (Chrisman, 2025).

Hypotheses

H1: Trust has a positive impact on the perceived usefulness
H2: Trust has a positive impact on the perceived ease of use
H3: Perceived usefulness has a positive impact on the attitude towards use
H4: Perceived ease of use has a positive impact on the attitude towards use
H5: Attitude towards use has a positive impact on the behavior towards use
H6: Behavior towards use has a positive impact on the Active use

Theoretical Framework

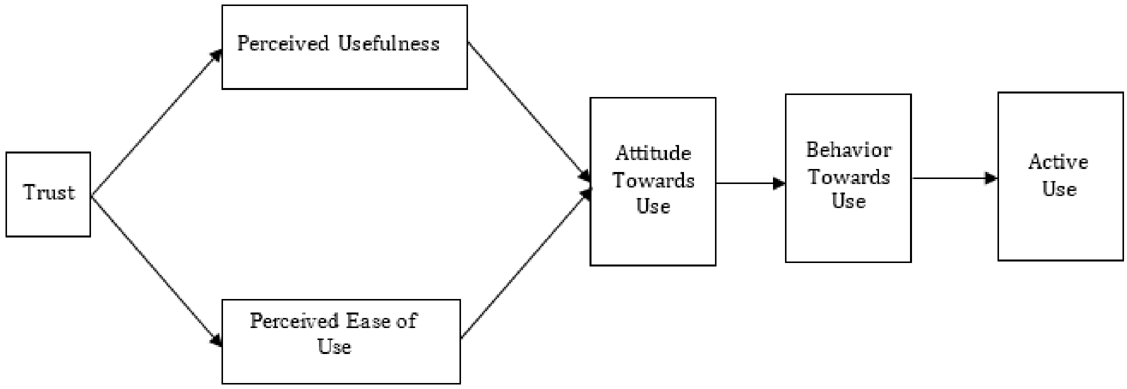

Figure No 1: Theoretical Framework

Material and Methods

The study takes it roots from the positivism paradigm which is a purely scientific paradigm which measures the realities in absolute quantitative sense and believe on measurable realities. As this study based on measurables realities quantities data was obtained from a closed ended questionnaire from 200 different patients of the district Gwadar who are suffering from different chronic diseases who mostly used different healthcare related applications for their treatments. Data was gathered through judgmental sampling where research has selected each respondent based on their knowledge and usage of healthcare mobile applications. The gathered data was analyzed while using an approach based on the Partial Least Square with a software named SmartPLS.

Data Analysis

Demographic Analysis

Demographic analysis is the explanation of the demographic characteristics of the participants' of the research. This table shows that there are a total of 345 respondents which have participated for the study and among which 231 participants are males and 114 participants are females. Further the table of the demographic shows the age wise distribution of the respondents which shows that 136 patients belong to age group of less than 35 years, 114 belong to the age group of 35 to 50 years and remaining 95 belong to age group above 50 years.

Table 1
Respondent Demography

Gander	Number	Percentage
Male	231	67%
Female	114	33%
Total	345	100%

Age Group	Number	Percentage
Less than 35 Years	136	39%
35 to 50 Years	114	33%
Above 50 Years	95	28%
Total	345	100%

Reliability and Validity

The validity and dependability of the data are displayed in Table 2, which also indicates how well the data is suited for additional investigation. Convergent validity and discriminant validity are two frequent tests used to measure validity, whereas items reliability and construct reliability are the two main tests used to assess reliability. The term "outer loading" refers to the metric used to assess an item's dependability. The outer loading cutoff value is 0.7 and above. The loading values for every item in the table below are higher than the threshold values. This demonstrates that every item has a sizable loading value. Cronbach alpha and composite reliability are the metrics used to assess construct dependability. Both measures have a threshold value of 0.7 or higher. According to the reliability and validity table, every construct has Cronbach alpha and composite reliability values over the threshold, proving that every study construct has attained dependability.

We assess the construct's validity in the following step of the validity process. Convergent validity is the first step of construct validity measurement, while discriminant validity is the second. Average Variance Extracted (AVE) is the statistical metric used to assess convergent validity. Although a number near 0.4 is acceptable in certain exceptional circumstances, the recommended threshold value for the AVE is 0.5 and above. According to the reliability and validity table, every construct has AVE values higher than the optimal threshold value of 0.5, proving that they have all attained convergent validity. The discriminant validity test is the next step in the validity process. Numerous metrics are employed to analyze discriminant validity; nevertheless, HTMT values are the most effective and optimal metric for discriminant validity. The HTMT threshold value is 0.85 or less, however under extreme circumstances, social scientists will accept any value below 1. According to the reliability and validity table, every construct in the model of this study has HTMT values below the optimal threshold value, indicating that all of the model's constructs have attained discriminant validity. Based on the results of the four tests mentioned above, it was determined that the data gathered for the study is genuine and trustworthy enough to be further examined in order to predict cause and effect.

Table 2
Reliability and Validity

Construct	Items	Loading	CA	CR	AVE	HTMT
Trust	TR1	0.823	0.787	0.817	0.617	0.734
	TR2	0.726				
	TR3	0.811				
Perceived usefulness	PU1	0.771	0.769	0.823	0.623	0.522
	PU2	0.781				
	PU3	0.749				
	PU4	0.773				
Perceived ease of use	PE1	0.722	0.819	0.919	0.719	0.634
	PE2	0.816				
	PE3	0.881				
	PE4	0.815				
	PE5	0.861				
Attitude Towards Use	AT1	0.781	0.778	0.871	0.671	0.733
	AT2	0.821				
	AT3	0.731				

Behavior Towards Use	BT1	0.734	0.772	0.849	0.649	0.674
	BT2	0.771				
	BT3	0.812				
Active Use	AU1	0.741	0.729	0.813	0.613	0.812
	AU2	0.734				
	AU3	0.712				

Regression analysis

Regression analysis n sample language we called it the statistical tool for the measurement of cause and effect. It is the most common tool used for the prediction of cause and effect relationships when the researcher is working on the primary data based on numbers. As this study is based on the cause and effect relationships, a technique based in the regression is the most suitable to be performed. In the regression analysis and p and t values are used a measure for the confirmation of the cause and effect relationship. The threshold value for the p is in the regression analysis is 0.05 or less. On the other hand the threshold value for the t value is 1.96 and above in the regression analysis for the significance of a relationship. The below table of the regression analysis shows that all the relationships based on the cause effect of this model are significant. This also shows that the model which we have formulated from the literature and past theories has been established.

Table 3
Regression Analysis

Hypothesis	Beta	T value	P value
H1: Trust positively influence the perceived usefulness	0.312	23.452	0.000
H2: Trust positively influence the perceived ease of use	0.421	12.932	0.000
H3: Perceived usefulness positively influence attitude towards use	0.312	11.811	0.000
H4: Perceived ease of use positively influence attitude towards use	0.091	7.123	0.000
H5: Attitude towards use positively influence behavior for use	0.081	6.371	0.000
H6: Behavior towards use positively influence the Active use	0.182	5.912	0.000

Model fitness

Model fitness is a statical analysis explain that how the model of the study is fit to be put into a different context other than the researcher. The measure used for the model fitness is the SRMR. The threshold value for an ideal fit model is 0.08 or less. The below table of the fitness shows a value of SRMR less than the threshold value which indicates that the model of this study is fit.

Table 4
Model Fitness

	Standard Model	Estimated Model
SRMR	0.075	0.079
d_ULS	0.745	0.784
d_G	0.312	0.321
Chi-square	398.453	403.853
NFI	0.823	0.842

Conclusion

Digital technology is spreading overall industry with a rapid growth, especially in the healthcare industry. This study aims to investigate how patient trust on the healthcare related mobile applications will leads towards their usage and what is the role of the technology acceptance model in this prospective. The result of this study shows that trust is one of the key factors which promotes the usage of the healthcare mobile applications through the technology acceptance model among the patients of District Gwadar. Results also shows that the usage of the healthcare related applications are mainly based on how much patients trust the application. More trust in the result and more usage of the application devices.

Recommendations

Although there are several limitations for the study but the main limitations were the population of the study was only limited to Karachi city and the mode of the study was purely based on the quantitative. Further researcher can enhaced the same model for the different ciities of Pakistan or overall cities of Pakistan to increase the generalizability of the findings. Further researcher also can explore the same model based on qulaitative analysis to better explore the model.

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