Received: 03 JUL 2025 | Accepted: 10 DEC 2025 | Published Online: 16 DEC 2025
Recoletos Multidisciplinary Research Journal Vol. 13 no. 2 (December 2025)
DOI: https://doi.org/10.32871/rmrj2513.02.07

Original Article

Determinants of Switching Intentions to E-Health Services among Healthcare Service Users: A Push–Pull–Mooring Perspective from Islamabad, Pakistan

Mariam Dilawar[1]*, Collins Dodzi Dzitse[1], Inaya Siddiqui[2]

[1] Silk Road School, Renmin University of China, Beijing, China

[2] Department of Governance and Public Policy, National University of Modern Languages, Islamabad, Pakistan

*Correspondence: maryamdilawar98@gmail.com

Abstract

Background: *Technology has reshaped healthcare delivery, particularly during and after the COVID-19 pandemic, by providing faster, safer, and more accessible alternatives to in-person care. However, there is limited evidence on the factors and behavioral drivers of e-health adoption in Pakistan. This study investigates the factors influencing switching intentions among healthcare users in Islamabad, Pakistan.*

Methods: *A quantitative cross-sectional survey was conducted to collect data from 930 healthcare service users in Islamabad, Pakistan. Structural Equation Modelling (SEM) was used to test the hypothesized relationships.*

Results: *The findings revealed that the push factors of inconvenience (0.251) and perceived risk (-0.221) and the mooring factors of trust (0.442) and switching cost (– 0.211) were significantly associated with switching intentions (p< 0.05), whereas the pull factors of ubiquitous care and opportunity for alternatives had no significant relationship with the switching intentions of healthcare service users.*

Conclusion: *The study concludes that inconvenience with traditional hospital services, risk perceptions, trust in e-services, and perceived switching costs are key drivers of e-health adoption in Islamabad. These findings underscore the need for user-centered digital health strategies that address both infrastructural and behavioral concerns to accelerate equitable healthcare transformation in the new era of technological development.*

Keywords

technology, e-health services, switching intentions, Push-Pull-Mooring theory, Structural Equation Modelling, Pakistan

INTRODUCTION

E-health is rapidly transforming worldwide. In 2024, more than 1.3 billion people are using digital services, ranging from online consultations to wearable devices (Statista, 2024). The global digital health market is valued at $172 billion and continues to grow as healthcare systems seek solutions for chronic disease management, efficiency, and equitable access (Grand View Research, n.d.). For both developed and developing countries, e-health represents not only technological innovation but also a strategic pathway for modernizing care delivery (Vimalananda et al., 2020). E-health encompasses diverse forms of care delivery, including synchronous interactions such as video consultations, and asynchronous exchanges such as appbased messaging, electronic health records, and mobile health monitoring (Reddy et al., 2021). Research highlights convenience, efficiency, and safety as primary advantages, particularly in reducing waiting times, enhancing continuity of care, and minimizing exposure to infections (Bokolo, 2021; Dahl et al., 2023). However, studies have also highlighted persistent barriers, including low digital literacy, concerns about privacy and data security, and a lack of trust in digital platforms (Liu et al., 2024). These factors contribute to the uneven adoption of e-health across contexts, particularly in low- and middle-income countries, where infrastructural limitations and low awareness further hinder its uptake (Khan et al., 2023; Liu et al., 2019).

Switching from traditional hospital visits to digital health services is not simply a matter of technological access but a behavioral decision shaped by multiple drivers. In service literature, switching intentions have been linked to dissatisfaction with current providers, perceived risks, and confidence in alternatives (Dogra et al., 2023; Galavi et al., 2022). In healthcare, common push factors include long waiting times, overcrowding, and poor hygiene, which motivate patients to seek alternatives (Zhang et al., 2023). Trust in digital platforms and institutional credibility can either encourage or inhibit adoption (Wu & Deng, 2019). Unlike commercial domains, such as e-commerce, healthcare decisions are high-stakes and risk-sensitive, which means that availability and convenience alone may not fully explain adoption patterns. Pakistan presents a pressing case study for investigating these dynamics in several ways. With per capita health spending at just $38 and only 1.2% of the Gross Domestic Product (GDP) allocated to healthcare (Khan et al., 2023), the system struggles with resource shortages, overcrowded facilities, and fragile physical infrastructure (Ahmed & Ahmed, 2018). The COVID-19 pandemic has further exposed these vulnerabilities, underscoring the need for scalable remote solutions to reduce infection risk and improve access (Bokolo, 2021; Elhadi et al., 2021). Despite the rapid emergence of digital health platforms, little is known about healthcare users' behavioural intentions to switch from traditional hospitals to electronic health services. The factors shaping these intentions remain underexplored, a gap that is particularly critical in Pakistan, where patient-centred adoption is essential for sustainable digital health integration.

Hence, this study sought to investigate the determinants of healthcare users' intention to switch to e-health services in Islamabad, Pakistan. Drawing on the Push–Pull–Mooring (PPM) theoretical framework, this study examines how push factors (e.g., inconvenience, perceived risks), pull factors (e.g., ubiquitous care, availability of alternatives), and mooring factors (e.g., trust and switching costs) interact with and shape switching intentions. By focusing on Islamabad, Pakistan, this study contributes to the theory by extending PPM into a high-stakes and resource-scarce healthcare context and practice in the Global South by offering actionable insights for digital health developers, hospital administrators, and policymakers seeking to advance inclusive healthcare transformation.

METHODS

Study Design

This study used a quantitative cross-sectional approach guided by the Push-Pull-Mooring (PPM) theoretical framework and the six hypotheses developed in the research model (Figure 1). The PPM framework, initially rooted in migration theory, has been widely adapted to research on consumer behavior and technology adoption. Bansal et al. (2005) introduced their application in service-switching behavior, laying the foundation for broader use in areas such as e-commerce, mobile services, and digital health (Longino, 1992). Recently, scholars such as Marx (2025) conducted meta-analytical reviews of PPM, highlighting its predictive power and the diversity of variables examined across studies. The premise of the PPM framework is that three factors shape individuals' decisions to switch from one option to another: push factors (negative aspects of the current service, such as dissatisfaction, inconvenience, or risks), pull factors (attractive features of the alternative, such as convenience, innovation, or availability), and mooring factors (personal or contextual conditions, such as trust or perceived costs, that either facilitate or inhibit change) (Dogra et al., 2023; Krishnan & Raghuram, 2023). In the context of e-health adoption in Islamabad, these forces provide a lens for analyzing the behavioral determinants of healthcare users' switching intentions.

In healthcare, push factors include inconvenience, such as long waiting times, rigid appointment systems, and the effort required to access services, which often prompt patients to consider alternatives, including e-health (Benoit et al., 2017). Similarly, perceived risks arising from poor hygiene, exposure to infections, and overcrowding increase discomfort with traditional hospitals, thereby strengthening the appeal of digital platforms (Galavi et al., 2022). These conditions are expected to influence switching intention based on the push dimension of the PPM.

H1: Inconvenience in traditional hospital services is significantly associated with healthcare users' intention to switch to e-health services in Islamabad.
H2: Perceived risk in traditional hospital settings is significantly associated with healthcare users' intention to switch to e-health services in Islamabad.

Pull factors emphasize the appeal of digital alternatives to traditional methods. Ubiquitous care, or the ability to access services anytime and anywhere, enhances the attractiveness of e-health platforms by offering timely and flexible medical attention (Snoswell et al., 2021). Similarly, the availability of alternative digital healthcare options empowers patients to compare providers and select services that best meet their needs (Alamri & Alshagrawi, 2024). These features highlight the role of e-health in drawing patients away from the conventional models of care.

H3: Ubiquitous care is significantly associated with healthcare users' intention to switch to e-health services in Islamabad.
H4: The availability of alternative healthcare options is significantly associated with healthcare users' intention to switch to e-health services in Islamabad.

Mooring factors, on the other hand, act as anchors that either support or restrain behavioral changes. Trust in e-health reflects patients' confidence in the competence, security, and reliability of digital platforms and providers, which reduces uncertainty and supports their adoption (Adjekum et al., 2018). By contrast, perceived switching costs, such as the time, effort, and disruption involved in moving from in-person care to digital platforms, can discourage patients from transitioning (Zhang & Wu, 2024). Together, these mooring conditions are expected to shape switching intentions.

H5: Trust in e-health platforms is significantly associated with healthcare users' intention to switch to e-health services in Islamabad.
H6: Perceived switching costs are significantly associated with healthcare users' intention to switch to e-health services in Islamabad.

The tested hypotheses (relationships among the variables) were captured using the simple conceptual model shown in Figure 1.

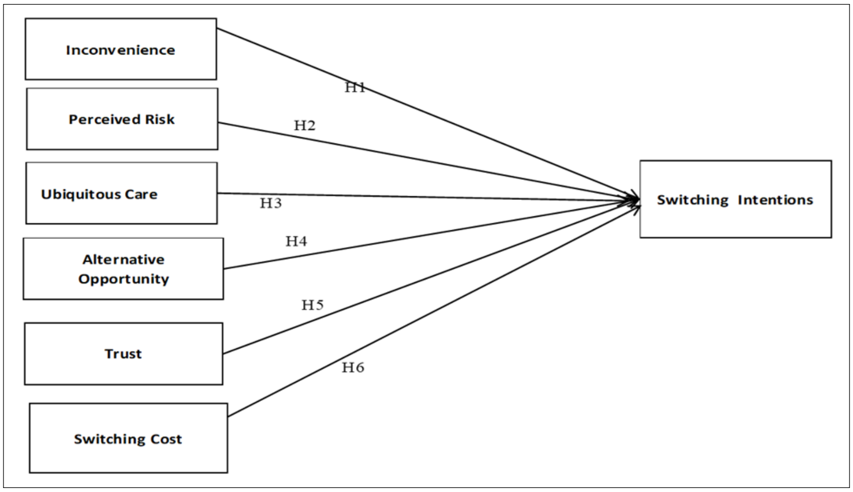


Figure 1. *Research model*

Study Variables and Instrumentation

A two-part questionnaire was developed in line with the independent constructs specified in the hypotheses: inconvenience (H1), perceived risk (H2), ubiquitous care (H3), alternative opportunity (H4), trust (H5), and switching cost (H6), and one dependent construct, "switching intentions". The first part of the questionnaire contained 25 items across these six independent constructs, with three questions each on inconvenience, perceived risk, ubiquitous care, alternative opportunity, and trust, and four items on switching costs (Adjekum et al., 2018; Dogra et al., 2023; Frishammar et al., 2023; Wu & Deng, 2019; Zhang et al., 2023). The final section of the first part measured switching intentions and contained six items (Benoit et al., 2017; Dogra et al., 2023). All items are measured on a five-point Likert Scale (1 = strongly disagree, 5 = strongly agree). By structuring the questionnaire in this manner, this study directly operationalized the research model's constructs, thereby enabling the empirical testing of the hypothesized relationships (H1–H6). The second part of the questionnaire elicited respondents' demographic characteristics, including sex, age, and education level.

Data Collection, Setting, Population

Using convenience sampling and a paper-based questionnaire, a cross-sectional survey was conducted among patients and hospital attendees in Central Islamabad, Pakistan, from June 6 to October 18, 2023. Data was collected from 18 medical facilities in Islamabad, including a mix of ten public-sector hospitals, five private hospitals, and three outpatient clinics. This strategy was designed to capture the diversity in patient experiences and reduce the risk of institutional bias that could arise from sampling a single site. Facilities were randomly selected to include both large tertiary hospitals and small clinics, reflecting the diverse character of healthcare access in the city.

At each site, the researchers approached potential participants in outpatient waiting areas. After providing a short description of the study, they were screened for eligibility (aged 18 years or older, recent users of healthcare services, and able to complete a questionnaire in English), and informed consent was obtained. Participation was voluntary, anonymous, and without any incentives. To reduce time-of-day bias, data collection was conducted across both morning and afternoon clinic sessions, including weekdays and weekends. Participants completed the questionnaires on-site and returned them in sealed envelopes to ensure confidentiality and to minimize the researcher's influence.

A total of 958 questionnaires were distributed to participants. After screening for eligibility and data quality (with more than 10% missing items, obvious straight lining, and failure of attention checks), 28 cases were excluded, yielding 930 usable responses (effective retention rate = 930/958 = 97.1%). While the high retention rate strengthens confidence in the dataset, it is worth noting that the convenience sampling design introduces potential selection bias, as the sample reflects only those actively seeking care at the participating facilities, rather than inpatients. Moreover, as the questionnaire was administered only in English, participation required a certain level of English literacy and proficiency. Consequently, the sample was skewed toward younger and more educated hospital attendees who were more likely to have formal schooling and competence in English. This also introduces a language–literacy limitation in our study, which means that the perspectives of older, less-educated, or non-English-speaking patients are likely underrepresented. Consequently, although sampling across multiple facilities enhances heterogeneity, the findings cannot be considered representative of the entire population of Islamabad or Pakistan; instead, they primarily reflect the views of urban and literate populations, rather than the full spectrum of healthcare users. Therefore, we suggest that the results should be interpreted as indicative of associations among variables in the context of hospital attendees, rather than generalizable estimates for all healthcare users. Future studies that use probability sampling across a broader population are required to validate and extend these findings. However, it is worth noting that out of the 930 valid responses, 217 were collected between June 6 and July 16, 2023. After a brief five-day pause, the remaining 713 valid responses were collected between July 22 and October 18, 2023.

Informed consent was obtained from all respondents. Ethical standards, which include maintaining anonymity and confidentiality, were strictly adhered to. Moreover, the instrument did not collect any personal information that could directly identify participants.

Data Analysis

To ensure methodological rigor, the dataset was analyzed in two stages. Exploratory Factor Analysis (EFA) was performed on the first 217 responses, while the subsequent 713 responses were used for Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). This split-sample approach minimized the risks of overfitting and strengthened the construct validation. Descriptive statistics and EFA were conducted using SPSS (Version 27). Exploratory factor analysis (EFA) was conducted to identify the underlying factor structure and retain the most salient items with loadings above the .50 threshold (Hair et al., 2019).

Subsequently, CFA and SEM were performed using AMOS (Version 26). CFA was employed to validate the factorial structure of the measurement model and to establish convergent and discriminant validity. SEM was then applied to test the hypothesized relationships between the constructs, with both standardized and unstandardized coefficients, standard errors, and exact p-values reported for transparency. Before proceeding to CFA and SEM, diagnostic tests were performed. Standard method bias was examined using Harman's single-factor test, which involves loading all items into an unrotated factor analysis. The results revealed that no single factor accounted for most of the variance (<40%) (switching intention = 25.55% as the highest contributor). Variance Inflation Factors (VIFs) and tolerance were examined to assess for potential multicollinearity and standard method bias. All VIF values were below 3.3 (Kock, 2015), and tolerance values exceeded 0.20 (Hair et al., 2019) (Table 3), indicating that multicollinearity was not a concern and standard method variance was unlikely to bias the results. Multivariate normality was assessed using Mardia's coefficient in AMOS. A critical ratio (C.R.) ≤ 5 is generally considered evidence of normality (Byrne, 2016). The obtained C.R. was 4.46, indicating that the data met the assumption of multivariate normality. Therefore, maximum likelihood estimation was used to conduct the CFA and SEM analyses (Preacher & Hayes, 2008).

RESULTS

An exploratory factor analysis (EFA) was conducted to identify the underlying structure of the measurement items. Seven distinct constructs were extracted (Table 1), each with an eigenvalue > 1.0 (Kaiser, 1960). All items with factor loadings of .50 or higher were retained, consistent with the recommended cutoffs for indicator reliability (Tabachnick & Fidell, 2019). The factor loadings ranged from 0.571 to 0.877, demonstrating good measurement quality for each dimension. Sampling adequacy was confirmed by a Kaiser–Meyer–Olkin (KMO) value of 0.738, while Bartlett's test of sphericity was significant ($\chi^2(300) = 3358.73$, $p < .001$), indicating the suitability of the data for factor analysis. Together, the seven extracted factors explained 71.95% of the total variance, which exceeded the recommended minimum of 60% for satisfactory construct representation (Hair et al., 2019; Kaiser, 1960).

Table 1. *Factorial Structure of Switching Intentions Constructs*

Latent constructs	Factor Loadings	Cron. α	Eigen-value	VE (%)	Mean	Std.
Ubiquitous Care		.815	3.537	14.14		
E-health consultation is available at any time of the day.	.741				3.69	.962
E-health consultation can be accessed from any location.	.828				3.73	.968
Even in urgent situations, e-health consultation is accessible without constraints.	.672				3.63	.972
Alternative Opportunity		7.81	2.393	9.57		
E-health consultations give me access to a wide range of doctors with different specializations	.745				3.93	.667
Through e-health platforms, I can consult doctors located outside my city or region	.795				4.08	.662
E-health services allow me to seek second opinions from multiple doctors before making decisions.	.821				4.07	.670
Switching Cost		.809	1.839	7.35		
Becoming proficient in using e-health consultation would require considerable effort from me.	.774				2.89	1.086
Switching from hospitals/clinics to e-health consultations would take too much of my time.	.733				2.54	1.053
Transitioning to e-health consultations would demand substantial effort on my part.	.589				2.55	1.044
Overall, shifting from traditional consultations to e-health would be troublesome.	.741				2.72	.970

Table 1. *continued*

Latent constructs	Factor Loadings	Cron. α	Eigen-value	VE (%)	Mean	Std.
Perceived Risk		.827	1.531	6.12		
Hospitals and clinics often lack proper sanitization, making the environment feel unsafe.	.653				2.70	1.122
I worry that the facilities in hospitals/clinics are unhygienic and expose patients to health risks.	.785				3.30	1.052
I feel anxious that I could contract communicable disease when visiting hospitals or clinics.	.821				3.30	1.012
Trust		.863	1.240	4.95		
I believe the process of e-health consultation is trustworthy.	.656				3.63	.815
I believe that doctors/service providers through e-health consultation are honest.	.699				3.50	.891
I believe that the doctor/service providers during e-health consultations will keep their commitment.	.711				3.48	.814
Inconvenience		.781	1.069	4.27		
Visiting physically to the clinics for consultation is time-consuming for me.	.571				3.35	1.141
Hospital or clinic visits involve extra effort, such as waiting in queues, completing registrations, or finding parking which stresses me	.592				3.82	.942
Attending consultations at hospitals or clinics feels inconvenient compared to digital alternatives	.588				3.44	1.092
Switching Intentions		.899	6.388	25.5		
I am determined to switch from traditional consultations to e-health services.	.877				3.61	.829
I plan to rely on digital health services for my medical needs in the future.	.816				3.57	.822
I expect to use e-health platforms frequently as part of my healthcare routine.	.852				3.53	.926
I intend to make e-health my primary choice for healthcare consultations.	.821				3.61	.884
I will recommend e-health consultations to others as a preferred alternative.	.835				3.39	1.052
Whenever possible, I will choose e-health services instead of physical hospital visits.	.872				3.51	1.041

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) = 0.738,
Bartlett's Test of Sphericity (X2 = 3358.730, df=300 and $p<0.001$); Total Variance Explained (VE)= 71.95%

Characteristics of the Sample

As shown in Table 2, among the 930 respondents, 496 (53.2%) were male, and 434 (46.8%) were female, indicating a balanced sex distribution in the sample. The sample was predominantly young, with 491 respondents (52.3%) aged between 18 and 30 years old. Participants aged 31–40 years accounted for 302 (32.1%), those aged 41–50 years for 94 (10.0%), and those aged 51 years and above for 45 (4.8%). In terms of educational attainment, more than half of the respondents (512, 54.5%) reported tertiary-level qualifications. A further 294 (31.3%) had completed secondary or high school education, and 124 (13.2%) reported basic education or other forms of training. These demographic characteristics suggest that the study captured a relatively young and well-educated sample, which is reflective of the population most likely to engage in digital health services.

Table 2. *Socio-Demographic Profile of the Sample*

Category	Number of Respondents	Percentage
Total Usable Responses	930	100%
Gender		
Male	496	52.8%
Female	444	47.2%
Age Group		
18-30 Years Old	491	52.3%
31-40 Years Old	302	32.1%
41-50 Years Old	94	10.0%
Over 50 Years Old	45	4.8%
Educational Level		
Tertiary	512	54.5
High School	294	31.3%
Basic or Other forms of training	124	13.2

Validity Assessment of Constructs

A confirmatory factor analysis (CFA) was conducted to validate the seven-construct measurement model. Model fit was acceptable: χ^2 (203) = 504.33, χ^2/df = 2.484, CFI = 0.948, GFI = 0.934, IFI= 0.955, NFI = 0.929, RMSEA = 0.045, SRMR = 0.041. All standardized factor loadings were significant ($p < .001$) and ranged from .598 to .941. Although one item under the inconvenience construct fell marginally below the recommended threshold of 0.60 (Kaiser, 1960), it was retained due to its theoretical importance and because removing it adversely affected the overall model fit and construct validity of the scale. Retaining theoretically meaningful items, even with slightly lower loadings, is consistent with the recommendations in SEM literature when the overall reliability and validity criteria are satisfied (Byrne, 2016). Composite reliability (C.R. = .891–.954), Cronbach's α (.876–.947), and average variance extracted (AVE = .782–.869) all exceeded the recommended thresholds, supporting internal consistency and convergent validity (Hair et al., 2011). Tolerance values (> .20) and VIFs (< 5) further indicated that multicollinearity was not a concern (Kock, 2015). In addition, the latent constructs exhibited strong internal consistency, with composite reliability, Cronbach's alpha, and average variance extracted (AVE) values surpassing the 0.50 threshold (Table 3).

Table 3. *Factorial Validity of the Structure of Switching Intentions Constructs*

Latent constructs	Std. Factor Loadings	Cron. α	CR	AVE	Tolerance	VIFs
Ubiquitous Care		.916	.928	.808	.736	1.359
E-health consultation is available at any time of the day.	.812					
E-health consultation can be accessed from any location.	.898					
Even in urgent situations, e-health consultation is accessible without constraints.	.771					
Alternative Opportunity		.931	.939	.854	.618	1.619
E-health consultations give me access to a wide range of doctors with different specializations	.807					
Through e-health platforms, I can consult doctors located outside my city or region	.810					
E-health services allow me to seek second opinions from multiple doctors before making decisions.	.868					

Table 3. *continued*

Latent constructs	**Std. Factor Loadings**	**Cron. α**	**CR**	**AVE**	**Tolerance**	**VIFs**
Switching Cost		.876	.891	.813	.884	1.131
Becoming proficient in using e-health consultation would require considerable effort from me.	.819					
Switching from hospitals/clinics to e-health consultations would take too much of my time.	.889					
Transitioning to e-health consultations would demand substantial monetary loss on my part.	.759					
Overall, shifting from traditional consultations to e-health would be difficult.	.809					
Perceived Risk		.892	.897	.782	.781	1.280
Hospitals and clinics often lack proper sanitization, making the environment feel unsafe.	.798					
I worry that the facilities in hospitals/clinics are unhygienic and expose patients to health risks.	.812					
I feel anxious that I could contract communicable disease when visiting hospitals or clinics.	.814					
Trust		.927	.939	.842	.849	1.178
I believe the process of e-health consultation is trustworthy.	.854					
I believe that doctors/service providers through e-health consultation are honest.	.801					
I believe that the doctor/service providers during e-health consultations will keep their commitment.	.816					
Inconvenience		.890	.954	.816	.615	1.625
Visiting physically to the clinics for consultation is time-consuming for me.	.853					
Hospital or clinic visits involve extra effort, such as waiting in queues, completing registrations, or finding parking which stresses me	.759					
Attending consultations at hospitals or clinics feels inconvenient compared to digital alternatives	.598					
Switching Intentions		.947	.951	.869		
I am determined to switch from traditional consultations to e-health services.	.924					
I plan to rely on digital health services for my medical needs in the future.	.922					
I expect to use e-health platforms frequently as part of my healthcare routine.	.941					
I intend to make e-health my primary choice for healthcare consultations	.911					
I will recommend e-health consultations to others as a preferred alternative.	.901					
Whenever possible, I will choose e-health services instead of physical hospital visits.	.896					

χ^2 =504.33, df = 203, CFI = 0.948, GFI = 0.934, IFI= 0.955, NFI = 0.929, RMSEA = 0.045 and SRMR = 0.041, χ^2/df= 2.484

Discriminant validity was assessed using two approaches. First, the cross-loadings of the indicator variables were inspected to ensure that each item loaded more strongly on its intended construct than on the others (Hair et al., 2011). Second, the Fornell–Larcker criterion was applied, whereby the square root of each construct's average variance extracted (AVE) was compared with its correlation with other constructs (Fornell & Larcker, 1981). As presented in Table 4, the square root of the AVE values (in bold) exceeded the inter-construct correlations in all cases, confirming discriminant validity.

Table 4. *Inter-Construct Correlation and the Square Root of AVE*

	UB	OA	SC	PR	TR	INCO	SI
Ubiquitous Care (UB)	**.898**						
Alternative Opportunity (OA)	.301	**.924**					
Switching Cost (SC)	.295	.249	**.906**				
Perceived Risk (PR)	.469	.311	.402	**.884**			
Trust (TR)	.341	.422	.424	.356	**.917**		
Inconvenience (INCO)	.191	.339	.354	.332	.328	**.880**	
Switching Intention (SI)	.303	.402	.326	.328	.337	0.398	**.932**

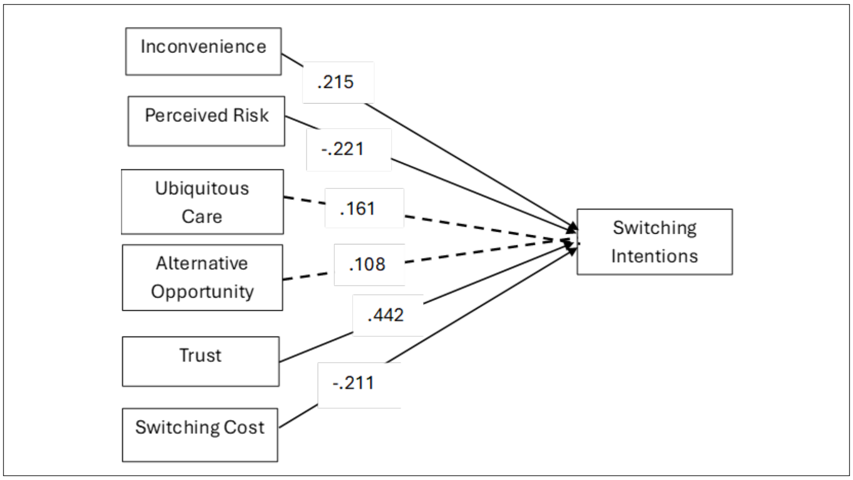
Structural Model and Hypothesis Testing

A structural equation model (SEM) was used to test the six hypothesized associations between the proposed determinants and switching intentions toward e-health services (Table 5). Both standardized (β) and unstandardized (B) coefficients, standard errors (SE), critical ratios (C.R.), and exact p-values were reported in the results. Multivariate normality was confirmed (Mardia's C.R. = 4.46); therefore, the Maximum Likelihood estimation was used. Although the data did not deviate from multivariate normality, bootstrapping with 5,000 resamples was applied to strengthen inference robustness. The bias-corrected 95% confidence intervals are presented in Table 5 (Hayes, 2013). The model demonstrated a good fit (χ^2 = 424.3, df = 185, χ^2/df = 2.29, CFI = 0.947, GFI = 0.964, IFI = 0.9322, NFI = 0.966, RMSEA = 0.051, SRMR = 0.046), indicating an acceptable correspondence between the model and the data (Figure 2).

The results indicate that inconvenience is positively associated with switching intention (H1: B = 0.312, β = 0.251, SE = 0.132, C.R. = 2.69, p = 0.003), suggesting that higher perceptions of inconvenience in traditional healthcare correspond to a greater intention to consider e-health alternatives. Perceived risk showed a significant negative effect (H2: B = 0.362, β = –0.221, SE = 0.148, C.R. = –2.133, p = 0.041), indicating that a higher perceived risk is associated with a lower intention to adopt e-health. Trust was positively related to switching intention (H5: B = 0.456, β = 0.442, SE = 0.182, C.R. = 3.441, p = 0.001), whereas switching costs were significantly negatively related (H6: B = – 0.342, β = – 0.211, SE = 0.072, C.R. = – 1.674, p = 0.012). These findings highlight that relational confidence and perceived barriers are the key correlates of switching decisions. In contrast, ubiquitous care (H3: B = 0.254, β = 0.161, p = 0.106) and alternative opportunities (H4: B = 0.332, β = 0.108, p = 0.224) were not significantly associated with switching intentions.

Table 5. *SEM Results Summary*

Hypothesis	Path	B (Unstd.)	β (Std.)	S. E	CR(t)	P-value	BC 95% Conf. Int.	Conclusion
H1	INCO → SI	.312	.251	0.132	2.69	0.003*	.10, .49	supported
H2	PR → SI	.362	-.221	0.148	-2.133	0.041*	-.61, -.04	supported
H3	UB → SI	.254	.161	0.063	2.462	0.106	-.02, .37	not supported
H4	OA → SI	.332	.108	0.166	1.312	0.224	-.08, .41	not supported
H5	TR → SI	.456	.442	0.182	3.441	0.001*	.21, .72	supported
H6	SC → SI	-.342	-.211	0.072	-1.674	0.012*	-.52, -.07	supported



Note: Significant association (—); Insignificant association (- - -)

Figure 2. *Final Structural Model based on Standardized Regression Weights*

DISCUSSION

The results of this study provide a nuanced understanding of the behavioral determinants influencing healthcare users' intentions to switch from traditional hospital visits to e-health services in Islamabad, Pakistan. The results showed a statistically significant positive association between inconvenience and switching intention ($\beta = 0.251$, $p = 0.003$), confirming Hypothesis 1, and underscoring dissatisfaction as a useful push factor in driving patients toward e-health adoption. This finding is consistent with previous studies, which have shown that long waiting times, overcrowding, and inefficient administrative processes often motivate patients to seek alternatives (Dogra et al., 2023). In Islamabad, where public healthcare facilities are chronically overburdened and under-resourced, inconvenience emerges not only as an operational flaw but also as a behavioral trigger that accelerates the search for digital solutions. This reinforces the PPM's proposition that push factors are central to explaining switching behavior, highlighting that hospitals must treat inefficiencies not as minor inconveniences, but as risks to patient retention. This underscores the importance of reengineering patient flow systems and integrating e-health consultations to ease congestion and reduce dissatisfaction-driven migration.

Perceived risk also showed a significant negative association with switching intention ($\beta = -0.221$, $p = 0.041$), confirming Hypothesis 2. This finding aligns with prior research, which identifies poor hygiene, exposure to infections, and overcrowding as key drivers of digital migration (Galavi et al., 2022; Reddy et al., 2021). The negative coefficient implies that, as risk perceptions regarding physical hospital environments increase, patients are more likely to consider switching to e-health services. The post-pandemic context in Islamabad, where concerns about sanitation and communicable diseases persist, likely amplifies this relationship. This emphasizes that perceived risk is a particularly decisive push factor in healthcare and is more influential than in commercial domains. Therefore, hospitals and policymakers must reduce risk perceptions through improved sanitation protocols, infection prevention measures, and transparent communication while simultaneously positioning e-health as a credible, safe, and regulated alternative. Institutional frameworks that certify digital platforms and enforce data security standards are vital for building public trust. Trust in e-health platforms emerged as the strongest determinant of switching intention ($\beta = 0.442$, $p = 0.001$), thus supporting Hypothesis 5. This aligns with the broader technology acceptance literature, which consistently identifies trust as a foundational element of digital engagement (Gong et al., 2025). In Pakistan, where interpersonal credibility and institutional reputation significantly influence healthcare choices, patients' willingness to adopt digital platforms is closely tied to their confidence in service providers' competencies, ethical standards, and system security (Ahmed & Ahmed, 2018). This underscores that mooring factors in PPM are not mere background conditions but can serve as decisive drivers of behavior in healthcare. Hence, developers must design secure, transparent, and user-friendly systems, and policymakers should establish accreditation and quality assurance schemes to validate digital health platforms.

Endorsement from credible institutions and visible service quality are essential for fostering adoption. Switching costs were also high and negative ($\beta = -0.211$, $p = 0.012$), confirming Hypothesis 6. This suggests that when users perceive the transition from in-person to digital care as effortful, disruptive, or risky, their likelihood of switching declines significantly. Conversely, when platforms reduce friction by making systems easy to learn, ensuring continuity with existing providers, and supporting user onboarding, the perceived costs diminish and switching intentions strengthen (Krishnan & Raghuram, 2023). This indicates that mooring factors within the PPM model act not as passive anchors, but as active deterrents that can constrain adoption, even when push factors are strong. Practically, this finding calls for minimizing friction in the adoption process by having hospitals and developers focus on seamless integration of e-health systems with existing patient records, providing onboarding support, and designing intuitive user interfaces. Policymakers can further reduce switching costs by promoting digital literacy campaigns and ensuring widespread awareness of the benefits and usability of e-health platforms.

In contrast, ubiquitous care ($\beta = 0.161$, $p = 0.106$) and alternative opportunities ($\beta = 0.108$, $p = 0.224$) were not significantly associated with switching intentions, disconfirming Hypotheses 3 and 4. This finding challenges the conventional assumption in PPM applications that attractive pull factors drive adoption. While convenience and accessibility are often assumed to be central motivators of digital health adoption (Barony Sanchez et al., 2022), the results suggest that users prioritize trust, safety, and continuity over flexibility and choice. This signals the need to reconceptualize pull factors in healthcare contexts, expanding them beyond accessibility and availability to include credibility, perceived safety, and institutional support. This means that simply expanding digital options or touting 24/7 availability will not induce switching unless users perceive these platforms as trustworthy, safe, and aligned with their expectations of quality care that they receive in person.

The results indicate that, in Pakistan's healthcare context, the adoption of e-health is shaped less by the availability of digital infrastructure and more by users' perceptions of dissatisfaction, risk, trust, and cost. Push and mooring factors were far more salient than pull factors, underscoring that structural shortcomings and relational confidence weigh more heavily on user decision-making than technological features. This confirms previous studies on service-switching behavior that emphasize dissatisfaction and trust as central determinants (Zhang et al., 2023), while contrasting with research on e-commerce and mobile services, where pull factors such as convenience and availability are often decisive (Bansal et al., 2005). This finding also aligns with research on health IT adoption, which suggests that trust and perceived risks are stronger predictors than accessibility alone (Adjekum et al., 2018; Wu & Deng, 2019). The findings therefore reinforce the relevance of the PPM framework but also highlight its limitations. While push and mooring factors were significantly associated with switching intentions, pull factors were not, suggesting the need for theoretical refinement. Thus, in healthcare, where emotional, clinical, and risk-related considerations dominate, PPM's traditional pull dimensions may be too narrow. Similar calls for adaptation have been made by scholars who argue that healthcare decisions require constructs beyond accessibility, including perceived clinical credibility and institutional assurance (Frishammar et al., 2023). Future adaptations of the framework could integrate elements from the Technology Acceptance Model or the Health Belief Model to better account for trust, safety, and literacy, thereby enriching its explanatory power in health contexts. These findings suggest that healthcare providers and hospital administrators must address the inefficiencies and risks that may deter patients, reframing them as behavioral triggers rather than operational issues. Digital health developers should recognize that trust is the cornerstone of adoption and prioritize secure, transparent, and user-friendly systems, while reducing switching costs through onboarding support and seamless system integration. Policymakers and public health planners should invest in digital literacy, public awareness, and quality assurance frameworks to reinforce institutional credibility. Ultimately, Pakistan's digital health transformation will be most effective through hybrid healthcare models, where traditional services and digital platforms work in tandem. Such models can improve access, efficiency, and responsiveness, while remaining aligned with the healthcare-seeking behavior of the population.

CONCLUSION

This study aimed to identify the determinants of e-health switching intentions in Islamabad, test the explanatory power of the push–pull–mooring framework, and draw implications for digital health strategies in Pakistan. The results demonstrate that inconvenience, perceived risk, trust, and switching costs are the central factors impacting switching intentions in Pakistan. The push and mooring factors showed a stronger association with switching intention, whereas the pull factors had a less significant impact. These outcomes not only offer theoretical implications for adapting PPM to trust-sensitive, resource-constrained healthcare contexts, such as Pakistan, but also align with the practical need for patient-centered strategies that reduce inefficiencies, build trust, and lower adoption barriers. Thus, future digital health models must be adapted locally rather than imported wholesale. Therefore, this study concludes that the adoption of e-health in Pakistan is shaped less by the availability of digital alternatives and more by the interplay between dissatisfaction, risk, trust, and perceived costs. This study underscores the importance of tailoring theoretical models and practical interventions to local sociocultural contexts to foster inclusive and responsive digital health transformations.

Author Contributions

M. Dilawar: Investigation, Writing - Original Draft, Writing – Review & Editing; **C. D. Dzitse:** Conceptualization, Formal Analysis, Visualization, Writing-Review, and Editing; **I. Siddiqui:** Investigation, Validation, Writing - Review & Editing.

Funding

This research received no external funding.

Ethical Approval

Informed consent was obtained from all subjects involved in the study.

Competing interest

The authors declare that they have no conflicts of interest.

Data Availability

The corresponding author will make the data available upon request.

Declaration of Artificial Intelligence Use

In this work, the author did not use generative AI or AI-assisted technologies in the preparation, analysis, or writing process.

REFERENCE

Adjekum, A., Blasimme, A., & Vayena, E. (2018). Elements of trust in digital health systems: Scoping review. Journal of Medical Internet Research, 20(12), e11254. https://doi.org/10.2196/11254

Ahmed, A., & Ahmed, M. (2018). The telemedicine landscape in Pakistan: Why are we falling behind? Journal of the Pakistan Medical Association, 68(12), 1820–1822. https://pubmed.ncbi.nlm.nih.gov/30504948/

Alamri, H. M., & Alshagrawi, S. (2024). Factors influencing telehealth adoption in managing healthcare in Saudi Arabia: A systematic review. Journal of Multidisciplinary Healthcare, 17, 5225–5235. https://doi.org/10.2147/JMDH.S498125

Bansal, H. S. (2005). "Migrating" to new service providers: Toward a unifying framework of consumers' switching behaviors. Journal of the Academy of Marketing Science, 33(1), 96–115. https://doi.org/10.1177/0092070304267928

Barony Sanchez, R. H., Bergeron-Drolet, L.-A., Sasseville, M., & Gagnon, M.-P. (2022). Engaging patients and citizens in digital health technology development through the virtual space. Frontiers in Medical Technology, 4, 958571. https://doi.org/10.3389/fmedt.2022.958571

Benoit, S., Klose, S., & Ettinger, A. (2017). Linking service convenience to satisfaction: Dimensions and key moderators. Journal of Services Marketing, 31(6), 527–538. https://doi.org/10.1108/JSM-10-2016-0353

Bokolo, A. J. (2021). Exploring the adoption of telemedicine and virtual software for care of outpatients during and after COVID-19 pandemic. Irish Journal of Medical Science, 190, 1–10. https://doi.org/10.1007/s11845-020-02299-z

Byrne, B. M. (2016). Structural equation modeling with AMOS: Basic concepts, applications, and programming (3rd ed.). Routledge.

Dahl, A. J., Peltier, J. W., & Swan, E. L. (2023). Anticipatory value-in-use in early-stage digital health service transformations: How consumers

assess value propositions before and after abrupt, exogenous shocks. Journal of Business Research, 163, 113910. https://doi.org/10.1016/j.jbusres.2023.113910
Dogra, N., Bakshi, S., & Gupta, A. (2023). Exploring the switching intention of patients to e-health consultation platforms: Blending inertia with push–pull–mooring framework. Journal of Asia Business Studies, 17(1), 15–37. https://doi.org/10.1108/JABS-02-2021-0066
Elhadi, M., Elhadi, A., Bouhuwaish, A., Bin Alshiteewi, F., Elmabrouk, A., Alsuyihili, A., Alhashimi, A., Khel, S., Elgherwi, A., Alsoufi, A., Albakoush, A., & Abdulmalik, A. (2021). Telemedicine awareness, knowledge, attitude, and skills of health care workers in a low-resource country during the COVID-19 pandemic: Cross-sectional study. Journal of Medical Internet Research, 23(3), e20812. https://doi.org/10.2196/20812
Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
Frishammar, J., Essén, A., Bergström, F., & Ekman, T. (2023). Digital health platforms for the elderly? Key adoption and usage barriers and ways to address them. Technological Forecasting and Social Change, 189, 122319. https://doi.org/10.1016/j.techfore.2023.122319
Galavi, Z., Pourasad, M. H., Norouzi, S., Jahani, Y., & Khajouei, R. (2023). Public usage, perceived usefulness, and satisfaction with e-health services in COVID-19 pandemic. Journal of Clinical Research in Paramedical Sciences, 11(2), e133719. https://doi.org/10.5812/jcrps-133719
Gong, S., Zhang, L., & Zhao, X. (2025). Association between e-health usage and consideration for clinical trial participation: An exploratory study on the mediating role of cancer-related self-efficacy and patient-centered communication. Digital Health, 11, 1–14. https://doi.org/10.1177/20552076251328598
Grand View Research. (n.d.). Digital health market size and share industry report, 2025–2030. https://www.grandviewresearch.com/industry-analysis/digital-health-market
Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage.
Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202
Hayes, A. F. (2013). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York, NY: Guilford Press
Kaiser, H. F. (1960). The application of electronic computers to factor analysis. Educational and Psychological Measurement, 20(1), 141–151. https://doi.org/10.1177/001316446002000116
Khan, S. J., Asif, M., Aslam, S., Khan, W. J., & Hamza, S. A. (2023). Pakistan's healthcare system: A review of major challenges and the first comprehensive universal health coverage initiative. Cureus, 15(5), e44641. https://doi.org/10.7759/cureus.44641
Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101
Krishnan, G., & Raghuram, J. N. V. (2023). Exploring factors and contextual applications of the push-pull-mooring (PPM) framework in switching intention: A systematic literature review. Multidisciplinary Reviews, 7(1), e2024003. https://doi.org/10.31893/multirev.2024003
Liu, F., Li, Y., & Ju, X. (2019). Exploring patients' consultation behaviors in the online health community: The role of disease risk. Telemedicine and e-Health, 25(3), 213–220. https://doi.org/10.1089/tmj.2018.0033
Liu, C., Wang, J., Chen, R., & Zhou, W. (2024). Exploring the influence of Chinese online patient trust on telemedicine behavior: insights into perceived risk and behavior intention. Frontiers in Public Health, 12, 1415889. https://doi.org/10.3389/fpubh.2024.1415889
Longino, C. F., Jr. (1992). The forest and the trees: Micro-level considerations in the study of geographic mobility in old age. In A. Rogers (Ed.), Elderly migration and population redistribution (pp. 23–34). Routledge.
Marx, T. (2025). The push-pull-mooring model of consumer service switching: A meta-analytical review to guide future research. Journal of Service Theory and Practice, 35(7), 1–29. https://doi.org/10.1108/JSTP-06-2024-0201
Preacher, K.J., & Hayes, A.F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40, 879–891. https://doi.org/10.3758/BRM.40.3.879
Reddy, A., Arthur, J., Dalal, S., Hui, D., Subbiah, I., Wu, J., Anderson, A. E., Castro, D., Joy, M., Nweke, C., Gogineni, M., Maddi, R., de Moraes, A. R., Shelal, Z., & Bruera, E. (2021). Rapid transition to virtual care during the COVID-19 epidemic: Experience of a supportive care clinic at a tertiary care cancer center. Journal of Palliative Medicine, 24(10), 1467–1473. https://doi.org/10.1089/jpm.2020.0737
Snoswell, C. L., Chelberg, G., De Guzman, K. R., Haydon, H. M., Thomas, E. E., Caffery, L. J., & Smith, A. C. (2021). The clinical effectiveness of telehealth: A systematic review of meta-analyses from 2010 to 2019. Journal of Telemedicine and Telecare, 29(9), 669–684. https://doi.org/10.1177/1357633X211022907
Statista. (2024). Digital health – Statistics and facts. https://www.statista.com/topics/2409/digital-health/
Tabachnick, B. G., & Fidell, L. S. (2019). Using multivariate statistics (7th ed.). Pearson.
Vimalananda, V. G., Orlander, J. D., Afable, M. K., Fincke, B. G., Solch, A. K., Rinne, S. T., Kim, E. J., Cutrona, S. L., Thomas, D. D., & Strymish, J. L. (2020). Electronic consultations (e-consults) and their outcomes: A systematic review. Journal of the American Medical Informatics Association, 27(3), 471–479. https://doi.org/10.1093/jamia/ocz185
Wu, H., & Deng, Z. (2019). Knowledge collaboration among physicians in online health communities: A transactive memory perspective. International Journal of Information Management, 49, 13–33. https://doi.org/10.1016/j.ijinfomgt.2019.01.003
Zhang, Q., Zhang, R., Lu, X., & Zhang, X. (2023). What drives the adoption of online health communities? An empirical study from patient-centric perspective. BMC Health Services Research, 23(1), 1-15. https://doi.org/10.1186/s12913-023-09469-6
Zhang, Y., & Wu, P. (2024). Continuous adoption of online healthcare platforms: An extension to the expectation confirmation model and network externalities. BMC Public Health, 24, 1-20. https://doi.org/10.1186/s12889-024-20072-0

How to cite this article:
Dilawar, M., Dzitse, C. D., & Siddiqui, I. (2025). Determinants of Switching Intentions to E-Health Services among Healthcare Service Users: A Push–Pull–Mooring Perspective from Islamabad, Pakistan. Recoletos Multidisciplinary Research Journal 13(2), 57-69. https://doi.org/10.32871/rmrj2513.02.07