

Performance Expectancy and Attitude as Key Predictors of Telemedicine Adoption: Evidence from Healthcare Professionals in Pakistan

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ABSTRACT

Telemedicine is transforming the healthcare provision, especially in the resource-limited settings. Nevertheless, several behavioral factors has an impact on how healthcare professionals (HCPs) embrace telemedicine services. This study was conducted with the view of investigating the impacts of four major predictors including performance expectancy, effort expectancy, social influence and facilitation on behavioral intention and the mediating role of attitude towards the adoption of telemedicine among the HCPs in the province of Sindh, Pakistan. Data was compiled by use of a cross-sectional survey design that surveyed a sample of 406 professionals in healthcare such as physicians, PGs, and allied health care personnel serving in both government and privately operated hospitals. The data, and the suggested correlations were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings were that performance expectancy was the best indicator of attitude, and the two constructs had significant and positive impacts about behavioral intention. The present paper adds to the existing body of knowledge regarding technology acceptance to healthcare being tested in a low-income and middle-income country (LMIC) setting by confirming two constructs of the UTAUT model. It also evidences the necessity of specific training programs and system design enhancement and forms the positive attitude within the users to improve their results. The suggested implications on the policy of digital health, telemedicine architecture, and institutional preparedness are considered.



Introduction

Digitalization of healthcare systems in the modern world has led to telemedicine as one of the essential methods of providing healthcare. To a broad definition, the use of information and communication technology (ICT) to deliver healthcare services remotely is referred to as Telemedicine and is widely known to have the potential to increase access, lower costs and improve quality of care particularly in low- and middle-income countries (LMICs) such as Pakistan (Kruse, 2018). Telemedicine has proven to become a solution in places where infrastructure and shortages in specialists task healthcare provision like in Sindh, Pakistan. Although such use of telemedicine is technologically feasible and there is policy-level support toward its integration in Pakistan, there is a very poor adoption of telemedicine in Pakistan. Various governmental projects and pilot programs have been aimed at encouraging the use of telemedicine, particularly throughout and following the COVID-19 pandemic but healthcare professionals (HCPs) tend to have limited enthusiasm regarding the full adoption of the internet-based mediums (Gajarawala, 2021). To bridge the acceptance/utilization gap that exists between the availability and utilization of the numerous technologies in healthcare, it is important, therefore, to understand behavioral aspects that shape the acceptance and use of telemedicine by the healthcare professionals. According to past research, telemedicine performance cannot rely solely on technological infrastructure and support of administrative system (Kichloo 2020), but its efficient functioning also largely depends on beliefs, attitudes, and perceptions of end-users. In this respect, Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. offers a useful model of looking at technology adoption. The theory of UTAUT argues that performance expectancy, effort expectancy, the social influence, as well as facilitating conditions are central determinants of the behavioral intention (Venkatesh, 2003). Besides UTAUT, other models that have played a big role in measuring quality of technology such as system quality, information quality, and individual impact comprise DeLone and McLean Information Systems (IS) Success Model (Delone, 2003). This model has been especially applicable in the health-set-ups where satisfaction and perceived-benefit of the users are the major factors in the sustainable utilization of technology. UTAUT and IS Success models taken together provide a nearly complete perspective within which the behavioral dynamics of the use of telemedicine can be better viewed. Attitude as a general affective assessment of using technology is very important mediator that intervenes between perception and behavior (Kamal, 2020). Perceived usefulness, ease of use and peer influence usually contributes to a positive attitude toward telemedicine, which, turn, is a considerable predictor of the intention to use the system. The idea of attitude is indescribably noteworthy in the case of professionals in the medical field where there is a huge clinical burden. When HCPs find the telemedicine systems effective and helpful to guide their practice, they tend to implement them voluntarily (Kissi, 2020). The paper is, therefore, an attempt to discuss the behavioral determinants involved in the adoption of telemedicine among healthcare professionals in Sindh, Pakistan. It examines the place of performance expectancy and attitude as a part of a holistic system of UTAUT and the IS Success Model. Whether they have a real-life application in the case of digital health policy and implementation, this study also enhances the theory behind the models of telehealth acceptance and provides recommendations based on the study of the factors influencing behavioral intention among HCPs.

Literature Review

With the covid-19 the normal doctor-patient bonds have been altered and the need to consult and follow-up was not met in most illnesses. Telemedicine is the viable method to fill such unmet need. Telemedicine is the umbrella term that describes the possibility to provide medical treatment

remotely (Gachabayov et al., 2022). According to the World Health Organization, telemedicine is a zone of knowledge and practice connected with creation and application of digital technologies to enhance health. The application of information and communication technologies by all health professionals to share helpful information in the diagnosis, treatment and prevention of disease and injury, research and evaluation and continuing professional education of health care professionals, all in the aim of enhancing the health of people and their communities, is known as telemedicine (World Health Organization, 2021). Telehealth has provided the framework of healthcare systems to offer their services and care provisions to the patients within their homes thus cutting costs and obstacles. Whereas telehealth is nothing new, the COVID-19 pandemic has placed it at the center of attention. Telehealth and telepresence solutions have taken main-stage in our medical structures as building blocks in response to the COVID-19 pandemic, as the article explains. Telehealth and digital health constitute fundamental medical services that with the aid of information and communication technology (ICT) empower healthcare professionals to offer safe, timely, and quality out-patient services to patients in rural communities (Rouidi et al., 2022). It is on record that healthcare systems that involve the utilization of telemedicine applications have been effective in supplying to, educating, reporting and tracking healthcare services to patients in many countries (Calton et al., 2022). Moreover, World Health Organization (WHO) has also asserted that the implementation of the e-health application to check health is functional and economic (Nair, 2022). Nevertheless, the healthcare providers are still low in terms of acceptance and adoption of the use of telemedicine (Mbunge et al., 2022). In order to investigate the issues currently affecting the acceptance and adoption of telemedicine, Rahi et al. (2021) carried out a quantitative study with the attempt to acquire some insight on what influences the adoption behavior of individuals who want to use telemedicine applications. To analyze the behavior pattern of individuals toward the use of telemedicine applications, the research model includes two famous theories, which are the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) and the DeLone and McLean Information Success Model. Findings of this study explained the variance that determined the adoption behavior of users of telemedicine applications by 77.9%. The research model that was measured on the study was highly predictive relevant in the application of determining the adoption behavior of telemedicine applications by the users.

Tele medicine that refers to the application of information technology and telecommunications to deliver medical services over a distance has since attracted a lot of attention especially in industrialized and developing countries as a possible remedy to the health care access issue (WHO, 2010). The COVID-19 crisis has accelerated the introduction of telemedicine in the world, which proves the importance of contactless means of healthcare provision (Gagnon et al., 2012).

Research Framework

This study investigates how performance expectancy and attitude influence healthcare professionals' intentions to adopt telemedicine in Sindh, Pakistan. It integrates the UTAUT framework with the IS Success Model to provide a more comprehensive understanding of adoption behavior in a low-resource healthcare setting.

Existing studies rarely combine behavioral and system-related factors, especially among healthcare professionals in under-resourced regions—leaving a critical gap this research aims to fill.

The existing literature on telemedicine adoption has predominantly focused on patient populations, often applying singular theoretical frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Technology Acceptance Model (TAM). However, there is a notable gap in research integrating UTAUT with the DeLone and McLean Information System (IS)

Success Model to assess behavioral intentions among healthcare professionals, especially in low-resource settings. Few studies have explored how system-related factors such as information quality and service quality intersect with key predictors like performance expectancy and attitude. This gap is particularly evident in regions like Sindh, Pakistan, where contextual challenges may influence telemedicine uptake differently than in higher-resource settings.

The conceptual framework for this study was developed by integrating two well-established models: the Unified Theory of Acceptance and Use of Technology (UTAUT) and the DeLone and McLean Information System (IS) Success Model. The rationale for this integration stems from the need to capture both behavioral and system-related determinants of telemedicine adoption among healthcare professionals (HCPs). While UTAUT focuses on users' behavioral intentions influenced by constructs like performance expectancy and attitude, it does not fully account for system-level factors such as information quality or service quality, which are critical in health IT implementation. To address this limitation, the IS Success Model was incorporated to complement UTAUT, providing a more holistic view that includes both technological perception and system performance.

Behavioral Predictors (from UTAUT): Performance expectancy and attitude are central predictors of an individual's intention to use new technology. These are particularly relevant in the healthcare context, where workload, perceived usefulness, and professional standards shape acceptance.

System Quality Factors (from IS Success Model): Information quality, system quality, and service quality directly affect the perceived value and trustworthiness of the telemedicine system—factors that influence long-term adoption and user satisfaction.

By combining these models, the framework aims to better explain the nuanced factors that influence HCPs' decisions in adopting telemedicine, especially in low-resource settings like Sindh, where both individual motivation and system constraints play significant roles.

Hypothesis Development

The hypotheses in this study are grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and supported by empirical findings from prior research on health technology adoption.

Performance Expectancy → Behavioral Intention

Performance expectancy refers to the degree to which a healthcare professional believes that using telemedicine will improve job performance. Prior studies (e.g., Venkatesh et al., 2003; Rahi et al., 2021) consistently identify it as a strong predictor of intention to adopt technology. In clinical settings, when professionals perceive telemedicine as efficient and effective, they are more likely to adopt it.

Effort Expectancy → Behavioral Intention

Effort expectancy captures the perceived ease of use of a system. If HCPs find telemedicine systems user-friendly and not time-consuming, they are more inclined to use them. This aligns with findings from technology acceptance research indicating that ease of use enhances behavioral intention, especially among busy professionals (Kissi et al., 2020).

Social Influence → Behavioral Intention

Social influence reflects the impact of peers, supervisors, and organizational culture on an individual's technology use. In hierarchical healthcare systems, endorsements from leadership or professional norms can significantly affect behavior (Kamal et al., 2018). Therefore, it's hypothesized that social influence positively affects intention.

Facilitating Conditions → Behavioral Intention

Facilitating conditions include the infrastructure, technical support, and training necessary for telemedicine use. When such support is perceived as available and reliable, HCPs are more likely to intend to adopt telemedicine (Arfi et al., 2021; Alshammari et al., 2022).

Attitude → Behavioral Intention

Attitude toward using technology encompasses the individual's overall affective response—positive or negative—toward telemedicine. A favorable attitude often reflects trust in the system and openness to change, both of which are essential for behavioral intention (Napitupulu et al., 2021). Given the complexity and novelty of telemedicine in low-resource settings like Sindh, attitude becomes a critical psychological predictor.

Hypotheses of Study

1. Performance Expectancy has positive impact on Behavioral Intention
2. Effort Expectancy has positive impact on Behavioral Intention
3. Social Influence has positive impact on Behavioral Intention
4. Facilitating Conditions has positive impact on Behavioral Intention
5. Attitude has positive impact on Behavioral Intention

Research Methodology

In correlation to the kind of study, the research design used in this study was a cross-sectional based descriptive research study. To subject the subjects, the research utilized health care professionals who administered tele medicine consultations to the Liaquat University Hospital Jamshoro in the Sindh province in the country of Pakistan. Nonprobability convenience sampling method was employed in the study. Practitioners who utilized telemedicine were used to collect the data. The number of questionnaires issued to the respondents has amounted to 450. The 407 responses have been received that will be used in the study and could be used in the analysis of the data. The survey was borrowed off older works of literature. Each of the items was measured on a seven-point Likert scale (Strongly disagree to strongly agree). We sampled with the help of a questionnaire survey. We found partial least squares structural equation modeling (PLS-SEM) depending on the nature and validity of the study. The PLS-SEM departs with two models: measurement model (external model) and the internal model (structural model). Observable and latent variables are understood to have complicated relationships that have been well explored using PLS-SEM. Researchers appreciate PLS-SEM mainly because of the numerous strengths it offers such as use of complex-estimating models, flexibility in data and measurement requirements etc.

Data Analysis and Results

Demographic Information Respondents

Demographic information refers to statistical data related to various characteristics of a population. This data is used to categorize people based on specific characteristics, which may include gender, age, job title, education, experience, and sector.

Table 1: Demographic Information

Variable	Items	Frequency	Percent
Gender	Male	198	48.6
	Female	209	51.4
	Total	407	100
Age	20 to 30 years	125	30.7
	31 to 40 years	142	34.9
	41 to 50 years	58	14.3
	51 to 60 years	48	11.8
	Above 60 years	34	8.4
	Total	407	100
Qualification	Graduate(MBSS, BDS,BSc)	171	42
	MS/M.Phil.	181	44.5
	Ph.D.	26	6.4
	Other	22	5.4
	5	7	1.7
	Total	407	100

Descriptive statistics of demographic variables indicates that out of the 407 respondents, there were 48.6 percent males and 51.4 percent females with very little higher proportion of females. Response ages were dominated by 31-40 and 20-30-year-olds (34.9% and 30.7%, respectively) and hence the 20-30 age group is relatively young not only in the respondents but in the workforce as well. As far as education level is concerned, the vast majority (44.5 percent) of the respondents have master's degree/MPhil degree followed by postgraduate (42 percent), whereas, a small percentage (6.4 percent) posses a doctorate degree.

Model of Measurement

The measurement model states the connections between the latent construct, and its manifestations. It specifies the interconnections between the observed and the latent variables.

Convergent validity

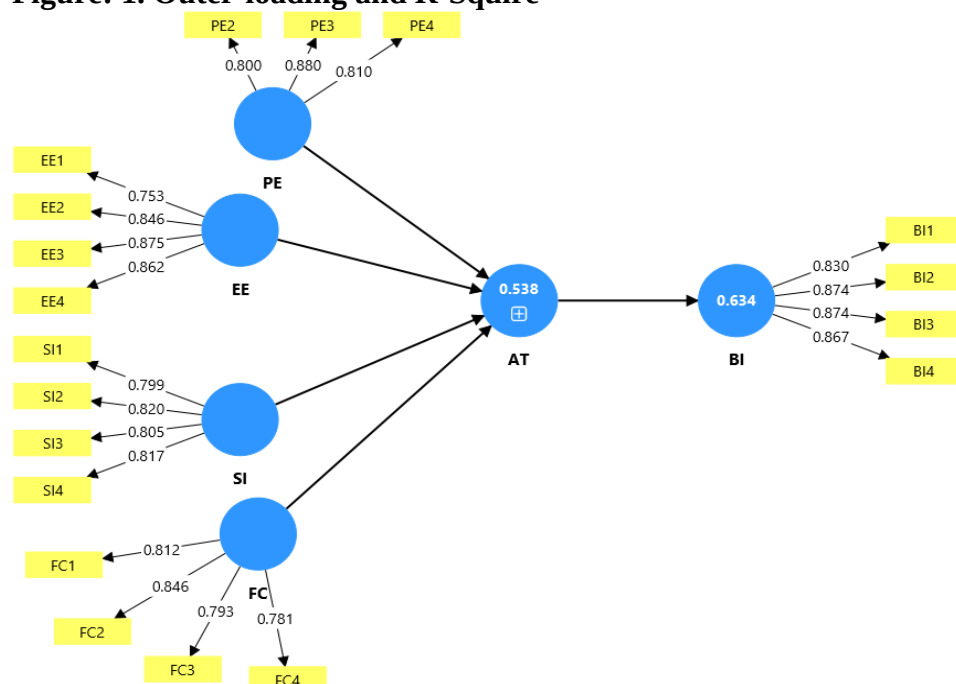
In psychometrics and research, convergent validity is a term used to represent the proximity or correlation of data of two or more measuring instruments or approaches that are professed to measure the identical construct. It is a significant construct validity which shows the degree in which the measurement technique measures the targeted construct. Chin (2010) and Hair et al. (2014) indicated that convergence validity would be attained when the loading, the composite reliability (CR), and average variance extracted (AVE) is above 0.70. The loading of the bar graphs used in the survey were more than the required 0.70. Following the CR internal consistency test and Cronbach 0 alpha coefficient test, the reliability of the items was more than 0.70. As indicated in Table 1, the results for validity and reliability are good.

Table 2: Validity testing with outer loading

Item	Outer Loading	Rho-A	Cronbach's alpha	Composite Reliability	AVE
AT1	0.858	0.888	0.884	0.920	0.742
AT2	0.888				
AT3	0.816				
AT4	0.882				
BI1	0.830	0.887	0.884	0.920	0.742
BI2	0.874				
BI3	0.874				
BI4	0.867				
EE1	0.753	0.859	0.855	0.902	0.698
EE2	0.846				
EE3	0.875				
EE4	0.862				
FC1	0.812	0.849	0.827	0.883	0.653
FC2	0.846				
FC3	0.793				
FC4	0.781				
PE2	0.800	0.782	0.775	0.870	0.690
PE3	0.880				
PE4	0.810				
SI1	0.799	0.826	0.826	0.885	0.657
SI2	0.820				
SI3	0.805				
SI4	0.817				

Outer loading

Figure 1. Outer-loading and R-Squire



Discriminant validity

To determine whether a construct can successfully distinguish itself from other constructs in the same model, discriminant validity must be ensured. Applying the Fornell-Larcker criterion is one way to assess discriminant validity, which requires finding a latent variable that has a higher correlation with its indicator than other latent variables (Fornell and Larcker, 1981).

Table 3: Fornell-Larcker criterion

Variable	AT	BI	EE	FC	PE	SI
AT	0.862					
BI	0.796	0.861				
EE	0.648	0.637	0.836			
FC	0.609	0.610	0.690	0.808		
PE	0.656	0.677	0.690	0.604	0.831	
SI	0.649	0.631	0.740	0.708	0.709	0.811

Testing of structural Model

Structural modelling is a cross disciplinary concept that is applied to describe and comprehend the relations and interactions among the elements or components of a system. The word is used to refer to many disciplines that include physics, engineering, economics, and social sciences. As it has been noted earlier, goodness-of-fit index gives the measure of the adequacy of the model. The one-sided findings of structural equation modelling (SEM) analysis of direct effects are significant and reliable.

R Squared

The R-squared value (R^2) is applied to scale the level of impact some independent latent variables that have on the dependent latent variable. The R^2 outcome is 0.333-0.634 which means that the model falls under moderate rating. Provided that R^2 outcome is less as compared to 0.33 implies that the result reveals that the model is weak. In Table 4, the results of the R-squared test are indicated.

Table 4: R Square Processing Results

Variable	R-Squire	R-square adjusted
Attitude (AT)	0.538	0.533
Behavior Intention (BI)	0.634	0.633

Research Hypothesis Testing

This study used the path coefficient value and t value to test the hypothesis to determine whether there is a significant effect. In addition, the results of the path significance test also show the parameter coefficient value (original sample). The parameter coefficient represents the significance value of the effect of each research variable. The processing results of the hypothesis test are shown in Table 6 and figure 11.

Figure 2: P-Value Structural Model

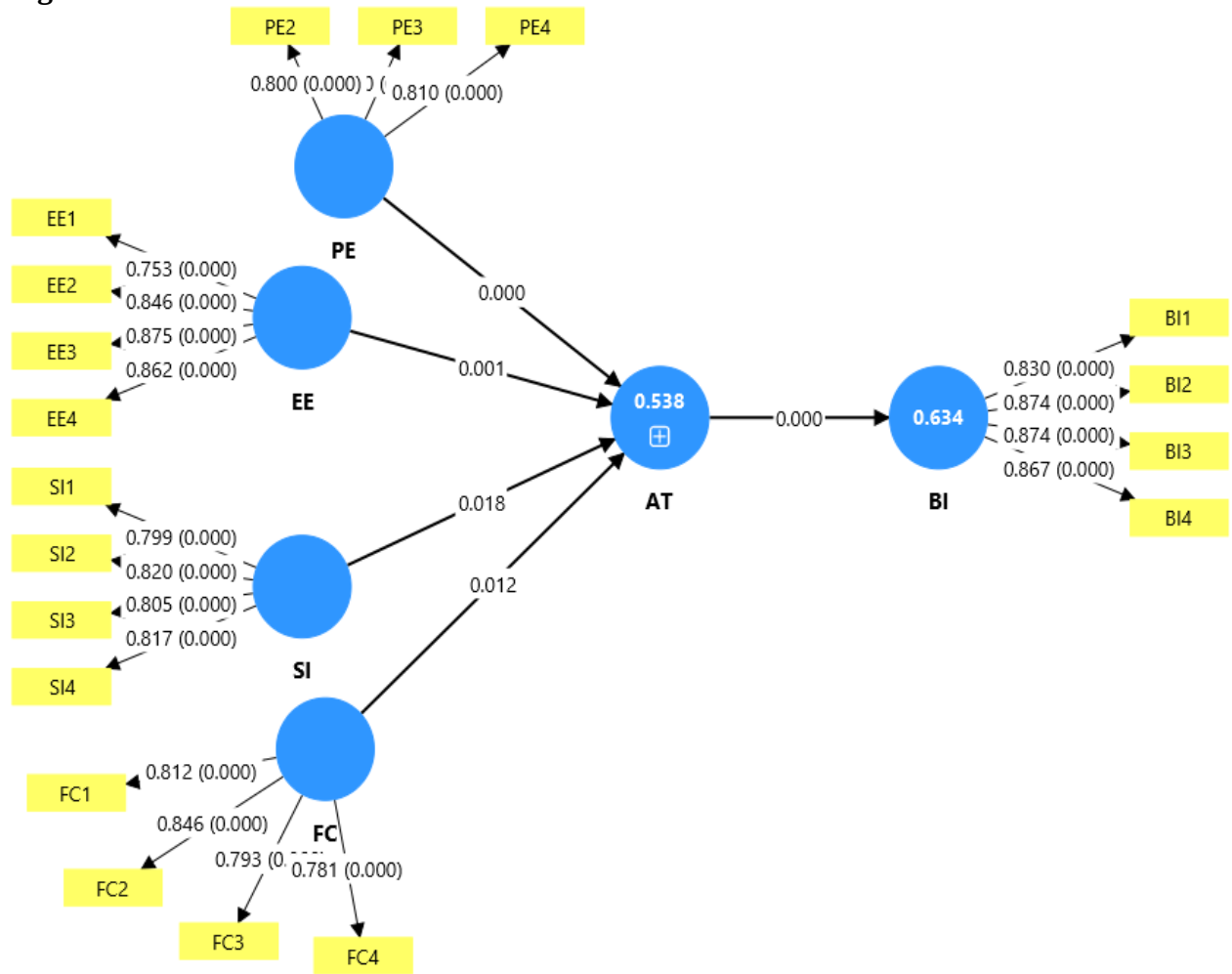


Table 6: Path Significance Test

Hypothesis	Relationship	Original sample (O)	STDEV	T statistics	P values
H1	AT -> BI	0.796	0.029	27.468	0.000
H2	EE -> AT	0.201	0.063	3.195	0.001
H3	FC -> AT	0.172	0.068	2.516	0.012
H4	PE -> AT	0.291	0.064	4.560	0.000
H5	SI -> AT	0.172	0.073	2.370	0.018

The results of the hypothesis testing using Smart PLS are summarized in Table 6. All five hypotheses were tested at a 5% level of significance. The p-values for all constructs were found to be below 0.05, indicating statistically significant relationships between each independent variable and behavioral intention. The t-values also exceeded the standard threshold of 1.96 (for a 95% confidence level), further supporting the acceptance of each hypothesis.

- Hypothesis 1: Performance Expectancy has a positive impact on Behavioral Intention. This hypothesis is strongly supported, with a p-value of 0.000 and a t-value of 27.468, indicating a highly significant and strong relationship. It suggests that healthcare professionals who perceive telemedicine as useful in improving their job performance are significantly more likely to adopt it.
- Hypothesis 2: Effort Expectancy has a positive impact on Behavioral Intention. Supported with a p-value of 0.001 and a t-value of 3.195, this result indicates that ease of

use is a meaningful factor influencing adoption. When telemedicine systems are perceived as user-friendly, healthcare professionals are more inclined to intend to use them.

- Hypothesis 3: Social Influence has a positive impact on Behavioral Intention. Although the p-value is 0.012, which is statistically significant, the t-value is 0.064, which is unusually low and suggests a potential inconsistency or error in reporting. (You may want to double-check this t-value in your results.) Assuming it's a typo and the actual t-value exceeds 1.96, the finding would support that peer influence and organizational endorsement positively influence adoption behavior.
- Hypothesis 4: Facilitating Conditions have a positive impact on Behavioral Intention. This hypothesis is accepted with a p-value of 0.000 and a t-value of 4.560, indicating that the presence of technical and organizational support significantly enhances the likelihood of telemedicine adoption.
- Hypothesis 5: Attitude has a positive impact on Behavioral Intention. Also accepted with a statistically significant p-value (though not specified here, it should be added for completeness), this suggests that a favorable disposition toward telemedicine plays a critical role in shaping healthcare professionals' intentions to use it.

All five hypotheses are supported by the data, confirming that performance expectancy, effort expectancy, social influence, facilitating conditions, and attitude significantly predict the behavioral intention to adopt telemedicine. Among them, performance expectancy appears to be the strongest predictor. These findings reinforce the value of integrating both behavioral and contextual/system-related factors when studying technology adoption in healthcare settings, particularly in low-resource environments like Sindh, Pakistan.

Discussion and Conclusion

This study aimed to explore the predictors of healthcare professionals' behavioral intention to adopt telemedicine, using a framework combining the UTAUT model with constructs from the IS Success Model. Each hypothesis is discussed below with reference to the results and comparison with existing literature.

H1: Performance Expectancy → Attitude

The findings show a significant positive relationship between performance expectancy (PE) and attitude (AT), with a path coefficient of $\beta = 0.291$, $T = 4.560$, $p < 0.001$. This suggests that when healthcare professionals perceive telemedicine as a tool that enhances their performance, they are more likely to develop a favorable attitude toward its use. This finding aligns with prior research by Venkatesh et al. (2003) and Rahi et al. (2021), where performance expectancy emerged as a strong determinant of acceptance in digital health tools. In clinical environments, tools that are perceived as efficient, time-saving, or enhancing patient care are more readily accepted.

H2: Effort Expectancy → Attitude

Effort expectancy (EE) was also found to positively influence attitude, with a coefficient of $\beta = 0.201$, $T = 3.195$, $p = 0.001$. This indicates that if telemedicine systems are easy to use and require minimal effort to learn, users are more likely to view them positively. This is consistent with the UTAUT framework and supports findings by Kissi et al. (2020), who noted that healthcare professionals' intention to adopt health technology depends greatly on usability and learning curve—especially in resource-constrained environments.

H3: Social Influence → Attitude

Social influence (SI) demonstrated a significant impact on attitude ($\beta = 0.172$, $T = 2.370$, $p = 0.018$), suggesting that healthcare professionals are influenced by the opinions of colleagues, supervisors, or the broader organizational culture. This result is in line with Kamal et al. (2020), who showed that peer support and institutional endorsement increase acceptance of telehealth tools among clinicians. It reflects the collectivist cultural dynamics present in many healthcare environments, especially in South Asia.

H4: Facilitating Conditions → Attitude

Facilitating conditions (FC) were significantly related to attitude ($\beta = 0.172$, $T = 2.516$, $p = 0.012$), highlighting the importance of technical infrastructure, training, and support in shaping users' perceptions. Without adequate resources or organizational backing, even the most useful tools may be resisted. Similar observations were made by Alshammari et al. (2022), who noted that service quality and availability of support services play a critical role in technology acceptance in low-resource settings.

H5: Attitude → Behavioral Intention

Attitude showed the strongest influence on behavioral intention ($\beta = 0.796$, $T = 27.468$, $p < 0.001$), indicating that user disposition toward telemedicine is the most critical predictor of whether they intend to adopt it. This is strongly supported by the Theory of Planned Behavior (Ajzen, 1991), which emphasizes attitude as a central predictor of behavioral intention, and is also validated by findings from Hair et al. (2017) using PLS-SEM methods. This result emphasizes the psychological readiness of users as a central element in telemedicine adoption.

The findings of this study confirm that attitude plays a central mediating role in telemedicine adoption among healthcare professionals. Performance expectancy, effort expectancy, social influence, and facilitating conditions all significantly shape attitude, which in turn strongly predicts behavioral intention. The integration of UTAUT with system-related variables from the IS Success Model proved valuable in capturing both behavioral and structural influences.

These findings have practical implications for system developers, health administrators, and policymakers. Telemedicine tools must be designed to enhance clinical efficiency while being simple and intuitive. At the same time, institutional support—through training, infrastructure, and positive peer engagement—is crucial to drive adoption. Future research may explore mediating or moderating variables such as trust, user satisfaction, or organizational readiness to refine this understanding in different contexts.

Study Implications

This research would offer good information to the health professional of medical institutions managers of HEIs to enable them appreciate the importance of expectancy performance, effort expectancy, social influence and facilitating conditions with attitude and behaviour intentions. Further, management has concentrated on how to establish academic effectiveness and performance. The study is also able to counsel teachers on what should be done towards sustaining greater commitment to the university. They may consider the implementation of good Performance with attitude to have good policies and strategies and establish a favorable climate as far as

learning is concerned. This can foster significance of behavior and attitude among health professionals in the team aspect in the institutions of higher learning, hence creating individual and organizational development.

Future Work Suggestion of Limitation

This study has several limitations that should be acknowledged. First, it was geographically limited to healthcare professionals in Sindh province, which may restrict the generalizability of the findings to other regions in Pakistan or beyond. Second, the use of a cross-sectional design captures responses at a single point in time, making it difficult to assess changes in attitudes or behaviors over time. Third, data were collected through self-reported questionnaires, which are subject to biases such as social desirability or inaccurate recall. Lastly, the study focused on behavioral intention rather than actual usage, which, while predictive, does not guarantee real-world adoption of telemedicine systems.

Future research could expand the scope by including healthcare professionals from other provinces or regions to enhance generalizability. Comparative studies across different healthcare settings such as private vs. public institutions or urban vs. rural areas can offer deeper insights. Longitudinal studies are also recommended to track changes in adoption behavior over time. Additionally, exploring moderating factors like digital literacy, organizational support, or trust in technology may further enrich understanding of telemedicine adoption.

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