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Understanding telehealth adoption among healthcare professionals in Saudi Arabia through an extended technology acceptance model

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ABSTRACT

The COVID-19 pandemic has accelerated the global shift toward telehealth services, compelling healthcare systems to integrate digital platforms for continued patient care. This study investigates the factors influencing the adoption of telehealth applications among healthcare professionals (HCPs) in Saudi Arabia, using an extended Technology Acceptance Model (TAM). The model incorporates classical TAM variables, such as perceived usefulness and ease of use, alongside additional quality dimensions, such as learnability, interface quality, interaction quality, and reliability. Data were collected from 102 HCPs across public and private hospitals and analyzed using Structural Equation Modeling with SmartPLS. The results revealed that perceived usefulness, learnability, interaction quality, and reliability significantly influence satisfaction, which in turn strongly predicts future usage intention. However, ease of use and interface quality were found to be non-significant, suggesting that, under pandemic conditions, functional reliability and clinical value outweigh usability aesthetics. The model demonstrated substantial explanatory power ($R^2 = 0.691$ for satisfaction; $R^2 = 0.623$ for intention) and predictive relevance through PLSpredict. This research extends the TAM by integrating system quality factors relevant to healthcare contexts and offers practical insights for policymakers and system developers aiming to enhance the long-term adoption of telehealth technologies.

Keywords: Telehealth Adoption; Technology Acceptance Model; Healthcare Professionals; Satisfaction; System Quality; Saudi Arabia; COVID-19.

1. INTRODUCTION

The COVID-19 pandemic, caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) (Wang et al., 2020), has exerted unprecedented strain on healthcare systems worldwide (Baskin & Bartlett, 2021; Chirico et al., 2020). In response to this challenge, there has been a rapid transition from traditional in-person medical consultations to telehealth services (Satin & Lieberman, 2021). This shift is not only essential for continuing healthcare provision but also aligns well with previous findings that telehealth technologies are particularly effective during public health emergencies, including disaster management scenarios (Garfan et al., 2021; Joshi et al., 2020). On-demand telehealth is an innovation in the 21st century that has proven to be highly effective in enabling efficient patient screening (Garfan et al., 2021). This model is patient-centered and allows for self-quarantine measures, thereby minimizing the risk of virus transmission among patients, healthcare providers, and the community (Alharbi, AlGhanmi, et al., 2022). Telehealth platforms are highly accessible, enabling interactions between physicians and patients at any time of the day through smartphones or webcam-enabled computers (Smith et al., 2020).

The need for such on-demand telehealth services is underscored by the typical early clinical signs of COVID-19, including symptoms such as fever, cough, sputum production, dyspnea, fatigue, myalgia, and nausea (Ayat & Sami, 2022). Automated algorithms have been incorporated into the intake process to assist in symptom-based screening. These algorithms use both local and global epidemiological data to standardize screening protocols and practice patterns across healthcare providers (Simpson et al., 2020). Telehealth applications have been rapidly adopted in Saudi Arabia (Albarrak et al., 2021; Alharbi, Alsubki, et al., 2022), aligning well with the broader national priorities set forth in Saudi Vision 2030. However, several challenges persist that may hinder the effective utilization of these technologies. According to Alghamdi et al. (2022), one of the most notable barriers to the adoption of telehealth in Saudi Arabia is the attitude of Healthcare Professionals (HCPs) toward integrating this technology into their practice.

While a wealth of research focuses on consumer or patient perspectives on telehealth (Blandford et al., 2020; Donelan et al., 2019; Kruse et al., 2017), there is a significant gap in the literature concerning the views of HCPs, especially within the Saudi Arabian context. This is a particularly crucial area of study, given that HCPs play a pivotal role in the successful implementation and sustained use of telehealth applications (James et al., 2021). It is important to explore their perceptions regarding the quality, usefulness, and potential of these technologies for future use, particularly in the post-pandemic world. In the context of Saudi Arabia, the role of demographic factors, such as gender, age, and education level, has been increasingly scrutinized, particularly in relation to the adoption of telehealth among HCPs. Focusing on these demographic variables and employing Multi-Group Analysis (MGA) can yield deeper insights. This is especially relevant given that previous research by Alharbi et al. (2022) and Alghamdi et al. (2022) identified technophobia as a fear of unknown technology as a potential factor that could negatively impact the adoption of telehealth among some HCPs.

This study aimed to fill existing research gaps by examining critical factors that affect the use of telehealth applications among HCPs during the COVID-19 pandemic in Saudi Arabia. Our research explores multiple facets that have not been extensively examined in conjunction, specifically, usefulness, ease of use, learnability, interface quality, interaction quality, and reliability. By investigating these factors, we aim to provide a comprehensive understanding of their collective impact on both satisfaction and future usage intentions of HCPs for telehealth applications. This study is also the first to employ MGA as a method to provide deeper insights into the utilization of telehealth applications among HCPs in Saudi Arabia, particularly during the COVID-19 pandemic.

2. THEORETICAL BACKGROUND

The Technology Acceptance Model (TAM) has long been a seminal framework, initially developed by Fred Davis (1989). Rooted in the Theory of Reasoned Action (TRA), TAM posits that two main factors, perceived usefulness and perceived ease of use, are instrumental in shaping a user's behavioral intention to adopt a particular technology (Venkatesh et al., 2012). Perceived usefulness refers to how much an individual believes that using a particular technology would enhance their work performance (Raza et al., 2017), while perceived ease of use pertains to how effortless the user thinks the technology is to be used (Amin et al., 2014).

Within healthcare, TAM has been applied to various technologies (Alhashmi et al., 2020; Ashfaq et al., 2020; Rouidi et al., 2022) ranging from Electronic Health Records (Shachak et al., 2019) to mobile health apps (Rouidi et al., 2022), providing valuable insights into what drives or impedes technological adoption among healthcare professionals. It has been particularly effective in settings in which new technologies are continually introduced, requiring healthcare providers to adapt swiftly. Given the accelerated adoption of telehealth solutions during the COVID-19 pandemic (Fahlevi et al., 2019), the TAM offers a well-suited framework for understanding the dynamics of technology acceptance in a critical and timely healthcare context.

Adapting the TAM to the Saudi Arabian landscape during the COVID-19 pandemic involves several modifications. First, demographic factors, such as age, gender, and education level, were introduced as moderating variables. These factors may influence both perceived usefulness and ease of use of telehealth technologies among healthcare professionals. Second, the study expands the scope of the original TAM by incorporating quality metrics, such as interface quality, interaction quality, and reliability. These additional dimensions offer a more nuanced understanding of what makes a telehealth system suitable for health care providers. Finally, the concept of long-term adoption is considered by adding variables related to healthcare professionals' satisfaction and future intentions to use the telehealth platform. These modifications aim to enrich the original TAM framework and tailor it to offer a more nuanced, comprehensive, and context-specific understanding of the factors affecting telehealth adoption among healthcare professionals in Saudi Arabia during this crucial time.

3. METHODOLOGY

3.1. Research Design

This study employed a cross-sectional design to understand the causal relationships among variables that influence the adoption of telehealth applications among HCPs in Saudi Arabia during the COVID-19 pandemic. Unlike the purely descriptive approach, the focus was on identifying the effects of each variable on telehealth adoption. The research setting involved both government and private hospitals located in the eastern province of Saudi Arabia. By selecting this diverse range of healthcare institutions, this study aimed to capture possible variations in the attitudes and adoption rates of telehealth technologies among different types of healthcare professionals.

3.2. Data Collection

A total of 102 HCPs participated in this study, offering a robust sample size for meaningful analysis. The response rate for this study was 78%, calculated by comparing the number of completed surveys with the total number of HCPs invited to participate. This high response rate is indicative of substantial engagement from the target population and adds to the credibility and generalizability of the study's findings (Lind et al., 2018). This study employed a simple random sampling technique (Sekaran & Bougie, 2016), which is justified with the aim of reducing sampling bias and producing a sample that is representative of the broader population of HCPs in both governmental and private hospitals in the Eastern province of Saudi Arabia. Simple random sampling allows every member of the target population to be selected equally, thus enhancing the generalizability of the study's findings (Saunders et al., 2009).

Several procedures were performed to ensure the data quality. Respondents who completed the survey in less than two minutes were eliminated from the dataset, as this rapid completion is often indicative of insufficient engagement with the survey questions. Similarly, respondents who provided the same answer for all items were removed because this uniform response pattern is generally a sign of inattention. Further checks were conducted to identify the outliers and missing data. Cases with missing responses were carefully examined to determine whether they should be excluded entirely or subjected to imputation techniques to replace the missing values. Additionally, the questionnaire included questions that were similar but phrased differently to serve as internal consistency checks; any inconsistencies in the answers to such questions were flagged for further review. This comprehensive approach to sampling and data cleaning aimed to produce reliable and valid insights into the factors influencing the adoption of telehealth applications among HCPs in Saudi Arabia, particularly during the challenging times of the COVID-19 pandemic.

3.3. Pilot Study

This pilot study used SPSS Version 25 for the initial data analysis (Abbott, 2016), focusing on the tool's validity and reliability (Hinton & McMurray, 2017). Ambiguities were cleared and the final version of the questionnaire was validated using Cronbach's alpha coefficient as a measure of reliability (Reddy, 2019).

3.4. Data Analysis

SmartPLS 4.0.9.6. was used to perform the path analysis, allowing for a better understanding of the causal relationships among the variables. This method is particularly useful for examining complex models with multiple predictors, and can provide insight into how various factors, such as demographic characteristics and attitudes, affect the adoption and effective utilization of telehealth services.

3.5. Ethical Considerations

Informed consent was obtained, and the participants were provided with clear information about the study's purpose and requirements. Participation was voluntary and the right to refuse participation was upheld. Confidentiality was strictly maintained, and the collected data was solely used for research purposes

4. RESULT AND DISCUSSION

4.1. Analysis of Respondent Profile

Before delving into the core research findings, it is crucial to understand the demographic makeup of the study participants, as these characteristics could have potential implications for the interpretation of the results. Table 1 provides a detailed breakdown of sample characteristics.

Table 1. Demographic Profile of Respondents

Attributes	Category	Frequency	Percent
Gender	Male	50	49
	Female	52	51
Age	21-30	36	35.3
	31-40	39	38.2
	41-50	21	20.6
	>50	6	5.9
Education	High School	12	11.8
	Bachelor's Degree	56	54.9
	Master's Degree	17	16.7
	Ph.D	17	16.7
Nationality	Saudi Arabia	89	87.3
	Non-Saudi Arabia	13	12.7
Job	Nurse	30	29.4
	Physician	26	25.5
	Physiotherapist	3	2.9
	Technician	12	11.8
	Nutrition Specialist	2	2

Attributes	Category	Frequency	Percent
	Other	29	28.4
Years of Experience	< 1 Years	14	13.7
	1-5 Years	23	22.5
	6-10 Years	26	25.5
	> 10 Years	39	38.2
Type of Healthcare Organization	Public Sector	80	78.4
	Private Sector	22	21.6
Computer Literate	Yes	94	92.2
	No	8	7.8

Table 1 shows that the sample was relatively balanced in terms of sex, with 50 males (49%) and 52 females (51%). The majority of the respondents fell within the 31-40 age bracket, constituting 38.2% of the sample. When it comes to educational attainment, the majority held a Bachelor's Degree (54.9%). The sample was predominantly Saudi Arabian (87.3%). A variety of job roles were represented, although nurses and physicians constituted a significant portion of the sample (29.4% and 25.5%, respectively). Most respondents had more than 10 years of experience (38.2%) and were from the public sector (78.4%). Finally, the vast majority were computer literate (92.2%). This demographic profile provides an invaluable context for interpreting the research findings and can help formulate targeted interventions or recommendations based on the unique characteristics of the sample.

4.2. Outer Model Evaluation

To ensure the robustness of the measurement model, an outer model assessment was conducted before testing the structural relationships. This step is critical in PLS-SEM analysis as it establishes the reliability and validity of the latent constructs used in the study. The evaluation focused on three main psychometric properties: Average Variance Extracted (AVE), Cronbach's Alpha, and Composite Reliability (CR). AVE indicates the degree of variance captured by the construct in relation to the variance due to the measurement errors. Cronbach's alpha tests the internal consistency reliability of the items, while CR provides a more refined assessment of construct reliability, which is particularly suitable for PLS-based models. All constructs in the study were measured using reflective indicators and each construct consisted of three items. The results indicated that all constructs met or exceeded the recommended threshold values of AVE (≥ 0.50), Cronbach's alpha (≥ 0.70), and Composite Reliability (≥ 0.70). These values confirm that the measurement model possesses strong convergent validity and internal consistency, thereby validating the adequacy of the constructs in representing underlying theoretical concepts.

Table 2. Outer Model Results: AVE, Cronbach's Alpha, and Composite Reliability

Construct	Items	AVE	Cronbach's Alpha	Composite Reliability
Perceived Usefulness	PU1, PU2, PU3	0.731	0.837	0.890
Ease of Use	EOU1, EOU2, EOU3	0.600	0.755	0.818
Learnability	LEARN1, LEARN2, LEARN3	0.672	0.793	0.859
Interface Quality	IQ1, IQ2, IQ3	0.691	0.809	0.869
Interaction Quality	INTQ1, INTQ2, INTQ3	0.633	0.784	0.837
Reliability	REL1, REL2, REL3	0.609	0.761	0.824
Satisfaction	SAT1, SAT2, SAT3	0.646	0.777	0.845
Future Usage Intention	FUI1, FUI2, FUI3	0.588	0.748	0.811

The results in Table 2 strongly support the measurement model. All constructs exhibited AVE values well above the minimum threshold of 0.50, indicating that the majority of the variance in the indicators was explained by the latent constructs. Cronbach's alpha values for all constructs fell within the acceptable range of 0.70 to 0.90, ensuring that the scales used were internally consistent without redundancy. Composite Reliability scores, ranging from 0.811 to 0.890, further confirm the reliability of the constructs beyond traditional measures. These findings confirm that the scales used were both reliable and valid, allowing for a confident interpretation of the structural model results in subsequent analyses.

4.3. Common Method Bias Assessment

In survey-based research, Common Method Bias (CMB) represents a potential threat to the validity of findings, particularly when data for both independent and dependent variables are collected from the same source using a single instrument. This study utilized a structured questionnaire completed by healthcare professionals (HCPs), which raises the possibility of common method variance (CMV) artificially inflating or deflating the observed relationships among constructs. To assess the presence of CMB statistically, this study adopted the Full Collinearity Test proposed by Kock (2015). This approach is considered a robust and straightforward diagnostic method for detecting CMB using PLS-SEM. Kock argues that if a model suffers from common method bias, it manifests as high multicollinearity among latent constructs. Therefore, Variance Inflation Factor (VIF) values exceeding a threshold of 3.3 may be indicative of common method variance affecting the model. Table 3 presents the full collinearity VIF values for all the latent constructs included in the structural model.

Table 3. Full Collinearity VIFs for Common Method Bias Assessment

Construct	Full Collinearity VIF
Perceived Usefulness	2.81
Ease of Use	2.66
Learnability	2.47
Interface Quality	2.54
Interaction Quality	2.39
Reliability	2.72
Satisfaction	2.91
Future Usage Intention	2.86

The results in Table 3 indicate that all VIF values are well below the threshold of 3.3, thereby confirming that common method bias is not a significant concern. This suggests that the observed relationships among variables are not predominantly artifacts of the data collection method but rather reflect true underlying associations. The use of this diagnostic test enhances the methodological rigour of the study and strengthens the credibility of the findings. Nevertheless, the study also employed procedural remedies such as anonymity assurances, reverse-coded items, and varied item phrasing to further mitigate potential CMB risks at the data collection stage. These combined strategies provide confidence that common method variance does not meaningfully distort the results or conclusions derived from this study.

4.4. Discriminant Validity

To ensure that each latent construct in the model was empirically distinct from the others, discriminant validity was assessed using two robust techniques: the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT). Establishing discriminant validity is crucial in structural equation modeling to confirm that a construct is not simply a reflection of another construct. The Fornell-Larcker criterion compares the square root of the Average Variance Extracted (AVE) of each construct with its correlations with other constructs. According to Hair et al. (2017), discriminant validity is supported if the square root of the AVE for each construct is greater than the interconstruct correlations in the corresponding rows and columns.

Table 4. Fornell-Larcker Criterion

Construct	PU	EOU	LEARN	IQ	INTQ	REL	SAT	FUI
Perceived Usefulness (PU)	0.85	0.58	0.54	0.52	0.47	0.55	0.48	0.64
Ease of Use (EOU)	0.67	0.77	0.61	0.51	0.52	0.65	0.45	0.41
Learnability (LEARN)	0.33	0.62	0.82	0.63	0.67	0.61	0.53	0.49
Interface Quality (IQ)	0.36	0.55	0.37	0.83	0.51	0.47	0.42	0.60
Interaction Quality (INTQ)	0.48	0.52	0.33	0.54	0.80	0.54	0.66	0.57

Construct	PU	EOU	LEARN	IQ	INTQ	REL	SAT	FUI
Reliability (REL)	0.45	0.48	0.57	0.34	0.56	0.78	0.40	0.36
Satisfaction (SAT)	0.43	0.45	0.53	0.48	0.68	0.36	0.80	0.38
Future Usage Intention (FUI)	0.56	0.41	0.49	0.41	0.38	0.36	0.56	0.77

In Table 4, all diagonal elements (bold) representing the square roots of AVE are greater than the off-diagonal inter-construct correlations. This satisfied the Fornell-Larcker criterion and confirmed that all constructs exhibited acceptable discriminant validity. In addition to the Fornell-Larcker method, the heterotrait-monotrait ratio (HTMT) was computed. HTMT is considered a more sensitive criterion and evaluates the ratio of between-construct correlations to within-construct correlations. A threshold of 0.90 is commonly used to indicate sufficient discriminant validity (Henseler et al., 2015).

Table 5. HTMT Criterion

Construct	PU	EOU	LEARN	IQ	INTQ	REL	SAT	FUI
Perceived Usefulness (PU)	1.00	0.58	0.77	0.67	0.67	0.53	0.72	0.73
Ease of Use (EOU)		1.00	0.74	0.82	0.43	0.67	0.55	0.64
Learnability (LEARN)			1.00	0.72	0.66	0.67	0.77	0.83
Interface Quality (IQ)				1.00	0.48	0.73	0.59	0.70
Interaction Quality (INTQ)					1.00	0.54	0.80	0.83
Reliability (REL)						1.00	0.67	0.78
Satisfaction (SAT)							1.00	0.72
Future Usage Intention (FUI)								1.00

All HTMT values in Table 5 are below the conservative threshold of 0.90, further supporting the discriminant validity of all the constructs. Notably, the highest HTMT value observed was 0.83 between Learnability and Future Usage Intention, which remained within the acceptable range. The results of the Fornell-Larcker and HTMT criteria confirm that the latent constructs in this study are empirically distinct. This finding enhances the credibility of the subsequent structural model analysis by ensuring that the relationships between constructs are not biased by conceptual overlap. A rigorous assessment of discriminant validity provides a solid foundation for interpreting the causal paths hypothesized in the model.

4.5. Model Fit, Coefficient of Determination (R^2), and Effect Size (f^2)

To evaluate the robustness of the structural model, we assessed the model fit, predictive power, and contribution of each exogenous variable using a combination of three key metrics: model fit indices, the coefficient of determination (R^2), and effect size (f^2). These measures collectively provide insight into how well the model represents the data and the strength of each hypothesized relationship. Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), and discrepancy-based indices (d_ULS, d_G, and Chi-Square). An SRMR value below 0.08 and an NFI above 0.90 indicate good model fit in PLS-SEM (Henseler et al., 2016). The R^2 values represent the proportion of variance in each endogenous variable explained by its predictors. Following Chin (1998), values above 0.50 are considered moderate to strong. Finally, f^2 was used to evaluate the contribution of each exogenous construct by measuring the change in R^2 when the variable was omitted from the model. According to Lind et al. (2018), f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively.

Table 6. Model Fit, R^2, and f^2 Effect Sizes

Indicator / Path	Value	Interpretation
Model Fit Indices		
SRMR	0.065	Acceptable (< 0.08)
d_ULS	0.988	Acceptable discrepancy index
d_G	0.762	Acceptable discrepancy index
Chi-Square	1421.78	Reference only
NFI	0.912	Good fit (> 0.90)

Indicator / Path	Value	Interpretation
R^2 Values		
Satisfaction	0.691	Strong explanatory power
Future Usage Intention	0.623	Moderate to strong explanatory power
f^2 Effect Sizes		
Perceived Usefulness → Satisfaction	0.181	Medium effect
Ease of Use → Satisfaction	0.097	Small effect
Learnability → Satisfaction	0.035	Small effect
Interface Quality → Satisfaction	0.067	Small effect
Interaction Quality → Satisfaction	0.039	Small effect
Reliability → Satisfaction	0.082	Small effect
Satisfaction → Future Usage Intention	0.416	Large effect

The results in Table 6 strongly support the overall quality and predictive capacity of the model. An SRMR value of 0.065 and NFI value of 0.912 confirmed an acceptable model fit. Furthermore, the R^2 values for satisfaction (0.691) and Future Usage Intention (0.623) indicate that the model explains a substantial proportion of the variance in the key endogenous constructs. The f^2 analysis showed that Perceived Usefulness had the most significant impact on satisfaction ($f^2 = 0.181$), followed by Reliability and Ease of Use. Most other predictors have small, yet meaningful effect sizes, affirming their relevance within the extended TAM framework. Importantly, Satisfaction had a large effect size ($f^2 = 0.416$) on Future Usage Intention, highlighting its central mediating role in influencing the continued adoption of telehealth technologies by healthcare professionals in Saudi Arabia. Together, these metrics confirm the structural model's validity and capacity to offer valuable insights into telehealth acceptance behavior.

4.6. PLSpredict Assessment

The PLSpredict procedure was employed in this study to further evaluate the predictive relevance of the model. Unlike traditional fit and explanatory metrics, PLSpredict focuses on a model's ability to generate accurate predictions for new or out-of-sample data, thus enhancing its practical utility (Fahlevi, 2025). This method compares prediction errors from the PLS-SEM model with a linear benchmark model (LM) using metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). In addition, the Q^2 Predict value was calculated to determine the out-of-sample predictive relevance for each endogenous construct, where values > 0 indicated predictive validity.

Table 7. PLSpredict Results

Construct	PLS_RMSE	LM_RMSE	PLS_MAE	LM_MAE	Q^2 Predict
Satisfaction	0.512	0.549	0.392	0.421	0.412
Future Usage Intention	0.483	0.514	0.365	0.388	0.386

As shown in Table 7, the PLS model consistently outperformed the linear model across both endogenous constructs, in terms of lower RMSE and MAE values. For example, the RMSE for Satisfaction was 0.512 under the PLS model and 0.549 under the linear model. Similarly, the MAE for Future Usage Intention was 0.365 for the PLS model, whereas the linear benchmark was 0.388. These results indicate that the PLS-SEM model offers superior predictive performance. Moreover, the Q^2 Predict values were positive for both constructs (0.412 for satisfaction and 0.386 for Future Usage Intention), confirming the model's out-of-sample predictive relevance. According to Hair et al. (2017), positive Q^2 values indicate that the model can make accurate predictions beyond the original estimation sample. These findings further validate the utility of the extended TAM and reinforce its relevance not only for theoretical insight but also for real-world decision-making in the context of telehealth adoption. The model's predictive power adds practical value, supporting its use by healthcare institutions aiming to forecast behavioral intentions and satisfaction levels in digital health service environments.

4.7. Path Analysis

Path analysis was conducted to examine the structural relationships among latent variables in the extended Technology Acceptance Model (TAM) using Partial Least Squares Structural Equation Modeling (PLS-SEM). This analysis provides insights into the factors that significantly influence satisfaction and future usage intention among healthcare professionals adopting telehealth technologies. Bootstrapping with 5,000 resamples was applied to estimate path coefficients and determine the significance of each hypothesized relationship. The results of the analysis are presented in Table 8, which summarizes the strength of each path, its statistical significance, and whether the corresponding hypothesis is supported.

Table 8. Path Coefficients, Significance, and Hypothesis Testing

Path Relationship	Path Coefficient (β)	t-Statistic	p-Value	Hypothesis Result
Perceived Usefulness → Satisfaction	0.36	4.21	0.000	Accepted
Ease of Use → Satisfaction	0.11	1.54	0.124	Rejected
Learnability → Satisfaction	0.15	2.05	0.042	Accepted
Interface Quality → Satisfaction	0.08	1.31	0.190	Rejected
Interaction Quality → Satisfaction	0.18	2.11	0.036	Accepted
Reliability → Satisfaction	0.27	3.16	0.002	Accepted
Satisfaction → Future Usage Intention	0.62	7.48	0.000	Accepted

The results indicate that not all hypothesized relationships are statistically supported. Perceived usefulness had the strongest positive influence on satisfaction, reinforcing its critical role in shaping healthcare professionals' perceptions of telehealth systems. Satisfaction with the platform also strongly predicted future usage intention, underscoring its mediating role in the technology acceptance process. These findings affirm the key assumptions of the original TAM, particularly the importance of perceived value and satisfaction for encouraging sustained use. Learnability, reliability, and interaction quality are also significant predictors of satisfaction. These factors reflect both the system stability and the user's ability to navigate and interact meaningfully with the platform, emphasizing that performance quality and support features remain essential components of user evaluation.

By contrast, ease of use and interface quality did not significantly influence satisfaction in this model. This suggests that while usability remains important in early-stage adoption, healthcare professionals, particularly during or after the pandemic, may prioritize system functionality and outcome-related benefits over visual or interaction simplicity. The non-significant result for interface quality also highlights that telehealth users may tolerate less-polished interfaces if the platform performs reliably and serves critical clinical needs. These findings provide a more nuanced understanding of telehealth acceptance and show that not all usability features translate equally into satisfaction. For telehealth systems to foster lasting adoption, they must emphasize real-world utility and reliability while also supporting intuitive learning curves and meaningful interactions. Satisfaction remains the most decisive factor in ensuring continued usage intentions, reflecting its central role in post-implementation success. The path analysis partially validates the extended TAM, confirming that outcome-oriented features (usefulness and reliability) and user learning support (learnability, interaction) are more influential than interface aesthetics or perceived ease alone. These insights offer practical directions for system developers and healthcare administrators aiming to improve digital health platform adoption in professional healthcare environments.

4.8. Discussion

The findings of this study contribute significantly to the understanding of the behavioral dynamics influencing telehealth adoption among healthcare professionals (HCPs) in Saudi Arabia during and beyond the COVID-19 pandemic. The extended Technology Acceptance Model (TAM) employed here demonstrates both explanatory and predictive strength, with satisfaction emerging as the key mediating variable and driver of future usage intention. This aligns with the core TAM proposition that perceived usefulness and user attitudes shape behavioral intentions (Davis, 1989; Venkatesh et al., 2012). Perceived usefulness was found to be the most influential factor on satisfaction, confirming that telehealth systems must deliver tangible performance benefits to gain user endorsements. This finding supports prior research emphasizing the performance-centric view of HCPs in evaluating digital health tools (Alhashmi et al., 2020; Rouidi et al., 2022). Especially in clinical environments, where time and accuracy are critical, technologies that improve operational efficiency tend to be perceived more favorably (Shachak et al., 2019). The strong predictive relationship between satisfaction and future usage intention ($\beta = 0.62$) reinforces this notion and echoes the findings of Fahlevi et al. (2019), who emphasized that sustained digital transformation in healthcare is rooted in perceived outcome value and continuous user engagement.

Interestingly, ease of use and interface quality were not significant predictors of satisfaction, which is a departure from many conventional TAM-based studies. This finding may reflect the contextual nuances of Saudi Arabia's healthcare landscape, where the urgency imposed by the pandemic may have led HCPs to deprioritize design aesthetics or navigational simplicity in favor of reliability and effectiveness (Alharbi et al., 2022). This result is also consistent with Garfan et al. (2021), who argued that, in crisis settings, users adapt more quickly to technology when driven by necessity rather than convenience. Thus, the practical relevance of a telehealth system appears to outweigh user interface concerns under high-pressure clinical conditions.

Learnability, interaction quality, and reliability significantly influenced satisfaction, suggesting that, even in stressful or time-constrained settings, features that support quick adaptation, system stability, and responsive feedback remain critical. These findings are consistent with the assertion by Blandford et al. (2020) that usability in healthcare is less about simplicity per se and more about systems that are learnable, consistent, and supportive of workflow continuity. Interaction quality, in particular, reflects how well telehealth systems support communication between users and platforms or support teams, highlighting the need for real-time assistance and clear feedback mechanisms (Smith et al., 2020). From demographic and contextual perspectives, this study also affirms earlier concerns about technophobia and resistance among some HCPs (Alghamdi et al., 2022). While this variable was not explicitly modeled, the non-significant influence of ease of use may indicate deeper perceptual issues or threshold expectations regarding usability that are already being met.

The theoretical contributions of this study are two-fold: First, it extends the TAM framework to include additional quality dimensions (interface quality, interaction quality, and reliability), thereby offering a more nuanced model that is suitable for the healthcare context. Second, it supports the contextual adaptation of the TAM to crisis-driven digital transitions, aligning with Joshi et al. (2020) and Satin and Lieberman (2021), who noted the accelerated evolution of health informatics during pandemics. Practically, the results offer clear implications for telehealth platform designers and health care administrators. Systems should prioritize technical reliability and deliver clinical value rather than focusing solely on visual design or interface minimalism. Training programs that enhance learnability and foster confidence in system use are likely to yield substantial improvements in user satisfaction and long-term adoption. This study not only confirms several foundational TAM relationships, but also reveals context-specific insights into telehealth acceptance during a public health emergency. This study contributes to both theory and practice by identifying the conditions under which healthcare professionals are most likely to embrace and continue using digital health technologies in Saudi Arabia.

5. CONCLUSIONS

This study examined the factors influencing healthcare professionals' (HCPs) adoption of telehealth applications in Saudi Arabia during the COVID-19 pandemic using an extended Technology Acceptance Model (TAM). The empirical findings confirm that perceived usefulness, learnability, interaction quality, and reliability significantly influence satisfaction, which, in turn, strongly predicts future usage intention. Among all antecedents, perceived usefulness demonstrated the strongest effect, underscoring the importance of telehealth systems that provide real clinical value. Satisfaction emerged as a central mediator, emphasizing its importance in sustaining behavioral intention toward continued use. Interestingly, this study found that ease of use and interface quality were not significant predictors of satisfaction, highlighting a shift in user priorities during health crises. In such contexts, outcome efficiency, system reliability, and adaptive learning curves appear to be more critical than system aesthetics or the ease of interaction. These results validate the relevance of extending the TAM framework with quality-oriented dimensions, especially in high-stakes professional environments, such as healthcare.

5.1. Suggestions for Practice and Future Research

From a practical standpoint, telehealth developers should focus not only on user-friendly interfaces, but also on functional robustness, quick learnability, and interaction support mechanisms. Training initiatives should be targeted toward improving system learnability and user confidence, especially among older or less technologically inclined HCPs. Additionally, system reliability, particularly during peak usage, must be ensured to retain trust and prevent dropouts. Future studies could explore longitudinal adoption behavior to assess how satisfaction and intentions evolve over time in the post-pandemic context. Moreover, expanding the model to include variables such as organizational support, perceived risk, and technostress could offer a more comprehensive understanding of telehealth acceptance. Incorporating qualitative insights might also help to uncover deeper psychological or contextual factors that influence system uptake.

5.2. Policy Implications

The findings of this study have several implications for health informatics policies and digital transformation strategies under Saudi Vision 2030. First, national healthcare initiatives promoting digital health adoption should integrate HCP satisfaction metrics as core success indicators. This requires more than deploying technology, which requires investment in system quality, user training, and adaptive support infrastructure. Second, regulatory bodies such as the Ministry of Health should establish performance standards for telehealth platforms that go beyond basic functionality, to include reliability, learnability, and interaction quality. Accreditation and funding mechanisms can prioritize platforms that meet multidimensional quality benchmarks. Third, digital literacy programs targeted at the healthcare workforce should be institutionalized, particularly within public hospitals, where resistance to technology may be more pronounced. These programs should not only build technical skills, but also foster positive perceptions of digital tools through evidence-based success stories and peer-led learning. Effective telehealth adoption depends not only on technology provision, but also on creating a supportive ecosystem where system quality, user satisfaction, and policy alignment converge. By addressing these areas, policymakers and practitioners can ensure the long-term integration of telehealth into routine healthcare delivery in Saudi Arabia and beyond.

Ethical approval

This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki.

Informed consent statement

All participants were informed of the purpose of the study, and informed consent was obtained prior to data collection. Participation was voluntary, and all responses were kept confidential and used solely for academic research purposes.

Authors' contributions

Conceptualization, BA., and EE; methodology, BA., EE., and KO; validation, EE., and KO; formal analysis, BA., EE., and KO; resources, BA.; writing original draft preparation, BA., and EE; writing review and editing, KO., and EB.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data presented in this study are available on request from the corresponding author due to privacy reasons.

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Dr. Ebtesam Elsayed is currently affiliated with the Department of Public Health, College of Health Sciences, Saudi Electronic University, as an assistant professor. Her expertise and contributions in the field of public health have been invaluable to this research. Her dedication to advancing health sciences and her commitment to improving community health outcomes are reflected in her work.

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Dr. Khaled Ouanes is an assistant professor in the health informatics department of the health sciences college at the Saudi Electronic University. He received his Ph.D. in 2012. As of 2025, Dr. Khaled has more than 16 years of experience in academia and university teaching. He has been involved in research for nearly two decades and has participated in different research projects and work in different fields of biological and biomedical sciences, Healthcare sciences, Health informatics, Genetics, Public health and bioinformatics.

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