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An Examination of Telemedicine Adoption: Unpacking the Determinants of Behavioral Intention through an Extended UTAUT

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Abstract: The COVID-19 pandemic has led to changes in people's lives, including the increased use of telemedicine services. Extending the UTAUT framework, the purpose of this study is to analyze the factors that influence behavioral intentions towards the adoption of telemedicine platforms and investigate the role of e-trust in promoting the use of telemedicine. A non-probability sampling approach was used to select a research sample of 204 respondents. The SEM-PLS model was used in this quantitative research. The population of this study is Halodoc users. The study found that performance expectancy, effort expectancy, facilitating conditions, and e-trust all had significant, direct, and positive effects on respondents' intentions to use telemedicine. The findings also revealed that social influence influences e-trust in online healthcare systems. No significant relationship between social influence and behavioral intention was found. The present study suggests a positive attitude toward technology can increase user intention in healthcare systems.

Keyword: Behavioral Intention, E-trust, Halodoc, Telemedicine, UTAUT.

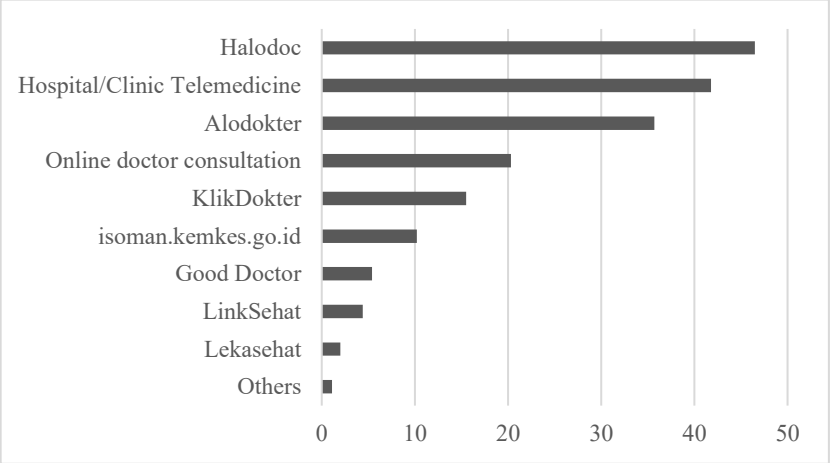
INTRODUCTION

The rapid spread of the COVID-19 virus infection around the world has resulted in many changes to the economic, social and health system sectors (Liu et al., 2020). With the development of information and communication technology in the industrial era 4.0, the healthcare industry is experiencing rapid and dynamic changes. In the healthcare industry, technologies such as the internet of things, cloud and fog computing, and big data have transformed e-Health and its entire ecosystem, pushing towards Healthcare 4.0 (Aceto et al., 2020).

Given the prolonged COVID-19 outbreak, there is a pressing requirement for medical personnel and patients to make use of telemedicine, which involves non-face-to-face care (Kim, 2021). Telemedicine uses technology to interact and offer healthcare remotely (Liao et

al., 2020). Telemedicine delivery is possible worldwide as smart devices and technology progress. This can greatly improve healthcare quality and efficiency while lowering costs (Bashshur, 2002). Telemedicine uses electronic data collection, analysis, distribution, and storage to improve health, prevent disease, treat patients, manage illnesses, and protect public health (Bashshur et al., 2009).

The Ministry of Health issued Telemedicine Indonesia (TEMENIN) for interhospital teleradiology, tele-ECG, and tele-USG in 2017. These services are available to all Indonesian citizens, and Halodoc is one of the TEMENIN health platforms. Based on the findings of a survey that was carried out by Katadata Insight Center (KIC), it is anticipated that Halodoc would become the most popular telemedicine application in Indonesia by the year 2022. The survey revealed that Halodoc currently has the highest percentage of telemedicine app users, reaching 46.5% of total users, with Alodokter coming in second at 35.7%.



Source: Katadata Insight Center, 2022

Figure 1. Most used telemedicine services & health facilities in Indonesia (2022)

Halodoc offers health information, teleconsultations with doctors, and online medicine purchases (Antarsih et al., 2022). Strong government support for telehealth will boost competitiveness in the health sector to develop a high-quality platform (Pusparisa, 2019). Most of this platform's users are millennials aged 20–30 (Dewanta et al., 2023). Based on Figure 1, Halodoc ranks number one in Indonesia, therefore this study focused on Halodoc users.

Telemedicine is growing in wealthier nations, and the COVID-19 pandemic has caused many developing nations to change their health care systems (Chakraborty et al., 2021). Telemedicine has a 70% failure rate due to lack of preparation (Mauco et al., 2018). According to Dewanta et al. (2023), 55% of Bali respondents who used digital services without interacting with doctors were still skeptical about their service, quality, and diagnosis. Doctor-patient connections may cause service distrust. The utility of Halodoc was questioned by 65%. The survey revealed many reasons to shun telemedicine apps. Lack of advertising, less popular, costlier, seldom used apps, less full functionality, less imaginative, poor service, and others may discourage digital health service use. These restrictions may prevent this app from becoming popular.

To successfully commercialize telemedicine services, one must understand their acceptance factors. To revive telemedicine adoption, these discoveries must be used to design methods. This study investigated the factors affecting telemedicine utilization. Using the Unified Theory of Acceptance and Use of Technology, this study achieved its goal. This method was chosen for its comprehensiveness and explanation (Barrane et al., 2018).

Venkatesh et al. (2003) developed UTAUT to explain how people use new information technology systems. This idea has been employed by e-health specialists to examine user behavior (Hoque & Sorwar, 2017; Kaium et al., 2020; Seethamraju et al., 2018). The UTAUT model has four (4) predictors of behavioral intention to adopt new technology, namely: performance expectancy, effort expectancy, social influence, and facilitating conditions and four moderating variables (age, gender, experience, and voluntariness of use). Age, gender, and experience remain moderating variables, but voluntariness has been eliminated, according to Venkatesh et al. (2012). It is assumed that the decision to adopt a new technology is inherently voluntary for end-users. Halodoc users were sampled to understand telemedicine adoption drivers and obstacles.

Utilizing technology requires more than just usefulness and convenience to promote behavioral intention, therefore, other elements, such as e-trust, are required to enhance this connection (Dewanta et al., 2023). A survey of 746 Chinese patients validated Zhang et al. (2019) mHealth adoption model based on an extended UTAUT. Performance expectancy, social influence, and trust in the application (e-trust) had the strongest total effects on behavioral intention to use mHealth apps, followed by privacy risk and facilitating conditions. Electronic-only connections without direct contact create e-trust (Tran & Vu, 2019). E-trust is also defined as consumers' beliefs and expectations that e-sellers are reliable and will perform their obligations faithfully (Giao et al., 2020). Previous research demonstrates that e-trust mediates social influence and behavioral intention (Dewanta et al., 2023; Hooda et al., 2022). Warsame & Ireri (2018) also found that age and gender mediate trust and behavioral intention.

Telemedicine, especially Halodoc, has expanded due to pandemics, which have shown how important digital health apps are. However, millennials still distrust the Halodoc app (Dewanta et al., 2023). This study examines how performance expectancy, effort expectancy, social influence, facilitating conditions, e-trust, and gender moderate the behavioral intention to use telemedicine platforms.

Literature Review and Hypothesis

1. Unified Theory of Acceptance and Use of Technology (UTAUT)

Technology has affected numerous industries, including health. Technology allows users to monitor and improve various aspects of their health at any time and place (Utomo et al., 2021). Many health studies have measured healthcare technology adoption using the UTAUT paradigm (Woldeyohannes & Ngwenyama, 2017; Wei et al., 2021). Venkatesh et al. (2003) predicts behavioral intention using performance expectancy, effort expectancy, social influence, and facilitating conditions.

2. Performance Expectancy

The performance expectancy measures how much patients expect telemedicine health services to improve their work performance (Venkatesh et al., 2003). Technology can reduce wait times, facilitate information access, and provide support in healthcare with limited facilities (Utomo et al., 2021). Previous research has demonstrated that performance expectancy increases behavioral intention (Barrane et al., 2018; Suki & Suki, 2017). Thus, this study posits that:

H1: Performance expectancy has a positive effect on behavioral intention to use telemedicine.

3. Effort expectancy

Effort expectancy is defined as 'the degree or extent of comfort users feel while using telemedicine health services' (Venkatesh et al., 2012). Octaviani et al. (2023) define effort expectancy in terms of the ease and simplicity perceived by customers in using the system. Telemedicine consumers need application effort expectation since medical emergencies are often urgent (Dewanta et al., 2023). Several research have shown that effort expectancy

favorably affects behavioral intention (Suki & Suki, 2017; Tusyanah et al., 2021). Therefore, we hypothesize that:
H2: Effort expectancy has a positive effect on behavioral intention to use telemedicine.

4. Facilitating conditions

Facilitating conditions is "the extent to which a patient believes organizational infrastructure makes telemedicine health services easier to use" (Venkatesh et al., 2012). Telemedicine users perform better with infrastructure, according to Nysveen & Pedersen (2016). Internet, cellphones, and user acquaintance with technology are needed for health support applications (Utomo et al., 2021). Previous research also shows that supportive conditions increase telemedicine behavior (Rahi et al., 2021; Rho et al., 2015). The present study hypothesized that:
H3: Facilitating conditions have a positive effect on behavioral intention to use telemedicine.

5. Social influence

Social influence refers to the degree to which a patient accepts the recommendations of significant others to embrace telemedicine health services (Venkatesh et al., 2012). Social influence boosts telemedicine adoption (Cho, 2016; Zhou & Li, 2014). Kaium et al. (2020) found that social impact affects m-health usage. Because social interactions, ideas, reviews, and peer opinions can dramatically impact online platforms and information, e-trust and social influence are linked. Previous study implies social influence boosts e-trust (Dewanta et al., 2023; Zhang et al., 2020). Similar research suggests that social impact does not affect e-trust (Yap & Lim, 2017). From this discussion, the following hypothesis is formulated:
H4: Social influence has a positive effect on behavioral intention to use telemedicine.
H5: Social influence has a positive effect on e-trust.

6. E-trust

Online situations are more complicated, making trust more important (Tran & Vu, 2019). E-trust reduces uncertainty and complexity in electronic market transactions and interactions, according to Tran & Vu (2019). M-health offers greater risks and uncertainties than normal health care, with trust, perceived dangers, and ambiguity being the major difficulties (Zhou et al., 2016). Customer trust serves as a crucial indicator in the adoption of telemedicine, highlighting its importance in this context (Tawil et al., 2023). Meng et al. (2019) used the trust transfer model to find that mHealth service trust positively affects intention to use. In accordance with this reasoning, the following hypothesis is postulated:
H6: E-trust has a positive effect on behavioral intention to use telemedicine.

7. Moderating variable: Gender

According to Venkatesh et al. (2003) research, one of the most important moderating variables in UTAUT is a person's gender. Gender theories say society and peer pressure determine gender differences, not genetics (Schmitz et al., 2022). Baron-Cohen et al. (2006) believe that empathy and systematization are intrinsic, with women being more empathic and men more superior. Gender differences in technological acceptability require further study (Lu et al., 2019). Reicher et al. (2021) propose that gender may affect telemedicine use, emphasizing the need for more research to eliminate gender disparities in implementation. Despite contradictory views and little health care research, this study seeks to illuminate gender differences in telemedicine usage.

METHOD

The proposed approach was tested by conducting an online Halodoc survey of a representative sample of the population. This study employed a non-probability sampling method, specifically the purposive sampling technique. Its efficacy in identifying specific individuals or groups from a small sample size made it the choice. In this case, the selected participants were Halodoc users. The SEM-PLS (Structural Equation Modeling Partial Least

Squares) method was used in this quantitative research. Since it does not require large sample numbers and is less sensitive to non-normal data distributions, Hair et al. (2011) recommend PLS-SEM for small samples. Complex models with several latent variables and prediction rather than explanation benefit from PLS-SEM (Hair et al., 2019).

A literature study was conducted to obtain the scales used in the measurement. Other than demographic information, all items were measured using a five-point Likert scale. According to Sumerli et al. (2023), Likert scale proves effective in capturing individual perceptions, enabling the measurement of a customer's views and attitudes. The study instrument's responses ranged from 'strongly disagree' to 'strongly agree'. Four items each in the instrument measure performance expectancy (Foon and Fah, 2011; Luarn & Lin, 2005; Venkatesh & Zhang, 2010), effort expectancy (Foon and Fah, 2011; Luarn & Lin, 2005; Venkatesh & Zhang, 2010; Sripalawat et al., 2011), social influence (Foon & Fah, 2011; Venkatesh et al., 2003; Venkatesh & Zhang, 2010; Sripalawat et al., 2011), e-trust (Chawla & Joshi, 2019; Jarvenpaa et al., 2000), and facilitating conditions (Venkatesh et al., 2003; Venkatesh & Zhang, 2010; Sripalawat et al., 2011), and three items measure behavioral intention (Luarn & Lin, 2005; Venkatesh & Zhang, 2010; Sripalawat et al., 2011).

Three screening questions—domicile, application possession, and latest use—ensured sample quality. The six questions in the last portion collected demographic data on respondents' gender, age, education level, occupation, average app spending, and service type. The survey had 204 valid replies. Table 1 summarizes respondents' basic information.

Table 1. Respondents' Demographic Profile

	Profile	Frequency	Percentage
Gender	Male	79	38.7
	Female	124	60.8
Age	18-20	14	6.9
	21-30	151	74.0
	31-40	30	14.7
	41-50	3	1.5
	> 50	5	2.5
Education	Senior High School	59	28.9
	Diploma	22	10.8
	Bachelor Degree	115	56.4
	Master Degree	8	3.9
Occupation	Student	102	50.0
	Civil servant	19	9.3
	Private employee	51	25.0
	Entrepreneur	14	6.9
	Self-employed	15	7.4
	Professional (Doctor, Lawyer, Lecturer, etc)	2	1.0
Average App Spending	< Rp 100.000	83	40.7
	Rp 200.000 – Rp 300.000	93	45.6
	Rp 300.000 – Rp 500.000	15	7.4
	Rp 500.000 – Rp 1.000.000	11	0.5
	> Rp 1.000.000	11	5.4
Service Type	Chat consultation with a doctor	98	48.0
	Purchase health products	73	35.8
	Homelab and vaccination	20	9.8
	Face-to-face consultation reservation	11	5.4
	Others	1	0.5

RESULTS AND DISCUSSION

To assess measurement validity and reliability, Hair et al. (2020) conducted a confirmatory composite analysis (CCA). Establish a composite reliability (CR) threshold of ≥ 0.7 for constructs (Hair et al., 2019). Every construct in this study has CR values > 0.7 and Cronbach alpha values > 0.7.

Table 2. Measurements Analysis

Construct/item	Loading	Cr. A	Rho A	CR	AVE	T-Statistics
First Order Construct						
Performance Expectancy		**0.843**	**0.855**	**0.896**	**0.684**	
I find using telemedicine is useful	0.885					37.321
Using telemedicine would improve my performance	0.697					10.290
Using telemdicine would save my time	0.876					30.302
I would use telemdicine anyplace	0.837					21.088
Effort Expectancy		**0.876**	**0.876**	**0.915**	**0.728**	
I find telemedicine is easy to use	0.859					27.595
Becoming skilled at using telemedicine is very easy for me	0.849					25.273
Learning to use telemedicine is easy for me	0.851					28.693
Interactions with telemedicine are clear and easy to understand for me	0.854					25.953
Facilitating Conditions		**0.883**	**0.886**	**0.919**	**0.740**	
I find it important to use telemedicine because it is convenient and easy to use	0.823					29.818
I have the knowledge necessary to use telemedicine	0.870					40.821
I have the necessary facilities to use telemedicine	0.880					41.019
The availability of help when I experience difficulties in using telemedicine	0.866					32.175
Social Influence		**0.806**	**0.826**	**0.873**	**0.634**	
People who are familiar with me think that I should use telemedicine	0.853					32.105
People who are important to me think that I should use telemedicine	0.871					38.466
People who influence my behavior think that I should use telemedicine	0.746					14.950
Most people surrounding with me use telemedicine	0.703					11.114
E-trust		**0.849**	**0.850**	**0.899**	**0.689**	
Doctors have the ability to provide telemedicine services well	0.849					36.631
Doctors have good experience so they are able to provide valid information	0.800					20.127
The people I interact with through telemedicine are trustworthy	0.826					26.775
I find that the telemedicine I use will always maintain its reputation	0.845					32.324
Behavioral Intention		**0.866**	**0.866**	**0.918**	**0.789**	
I intend to use telemedicine in the future or whenever I need remote medical care from professionals	0.872					33.661
I would say positive things about telemedicine to others	0.897					43.363
I would recommend telemedicine to others	0.894					45.211

The construct reliability parameters exceeded thresholds. Positive correlation between indicators within a dimension is convergent validity. Hair et al. (2022) recommend a loading factor of 0.708 and an AVE of 0.5. Table 2 shows that all construct-measuring items had a loading factor greater than 0.708 and an AVE greater than 0.5, showing convergent validity.

According to Fornell and Larcker (1981), discriminant validity is the ability to identify a measure from theoretically unrelated ones. Henseler et al. (2015) tested PLS-SEM discriminant validity using HTMT. Table 3 shows all square root AVE values below 0.90, demonstrating discriminant validity.

Table 3. Discriminant Validity With HTMT

	BI	EE	ET	FC	PE	SI
BI						
EE	0.833					
ET	0.909	0.780				
FC	0.904	0.831	0.863			
PE	0.810	0.858	0.768	0.792		
SI	0.668	0.581	0.826	0.723	0.586	

Next, f^2 was assessed to determine the effect size of independent variables, independently of sample size (Benitez et al., 2020). The effect size can be categorized as small ($0.02 < f^2 < 0.15$), medium ($0.15 < f^2 < 0.35$), or large ($f^2 > 0.35$) (Manley et al., 2021). Table 4 displays a range of effect sizes for exogenous variables, from 0.001 to 0.150, showing medium strength for independent variables on behavioral intention. The effect size of the four main predictors and e-trust as an independent variable on behavioral intention is quite small, while the f^2 value for the relationship between social influence and e-trust is large with values of 0.899.

Table 4. Hypothesis Testing Results

Path	B	SD	T-Value	Interval Bias Corrected	P-Value	F^2	Result
Performance Expectancy → Behavioral Intention (H1)	0.126	0.069	1.918	(0.019, 0.233)	0.028	0.023	Supported
Effort Expectancy → Behavioral Intention (H2)	0.157	0.069	2.277	(0.046, 0.270)	0.011	0.032	Supported
Facilitating Conditions → Behavioral Intention (H3)	0.342	0.083	4.133	(0.206, 0.480)	0.000	0.140	Supported
Social Influence → Behavioral Intention (H4)	-0.025	0.057	0.433	(-0.113, 0.072)	0.333	0.001	Rejected
Social Influence → E-trust (H5)	0.688	0.050	13.806	(0.595, 0.761)	0.000	0.899	Supported
E-trust → Behavioral Intention (H6)	0.353	0.075	4.702	(0.238, 0.483)	0.000	0.150	Supported

Path coefficients, explained variance, effect size, t-values, and 5.000-sample bootstrapping were used to test hypotheses UTAUT theory predicted behavioral intention in Halodoc. Performance expectancy, effort expectancy, social influence, and facilitating conditions comprise UTAUT. E-trust is added to this UTAUT framework as an antecedent of the dependent variable. Path coefficient analysis (Figure 2, Table 4) reveals that performance expectancy ($\beta = 0.126$, t-value = 1.918, p-value = 0.028), effort expectancy ($\beta = 0.157$, t-value = 2.277, p-value = 0.011), facilitating conditions ($\beta = 0.342$, t-value = 4.133, p-value = 0.000), and e-trust ($\beta = 0.353$, t-value = 4.702, p-value = 0.000) have a positive and statistically significant influence on behavioral intention. However, social influence does not appear to have any effect on behavioral intention ($\beta = -0.025$, t-value = 0.433, p-value >

0.05). Additional examination reveals that social influence has a positive impact on e-trust (β = 0.688, t-value = 13.806, p-value = 0.000).

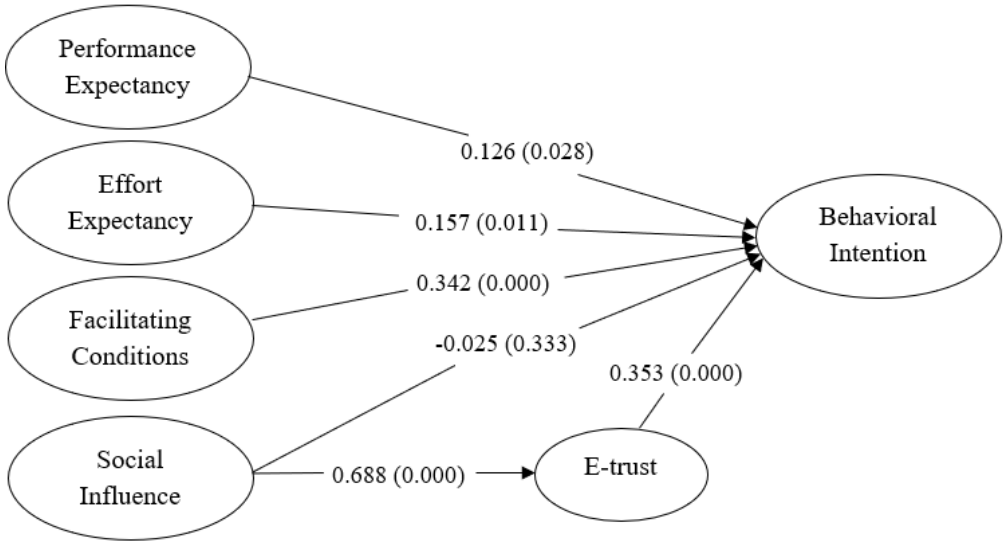


Figure 2. Conceptual Model With Results

Examine the model's coefficient of determination (R^2). This coefficient shows how much volatility in the endogenous variable may be explained by all connected exogenous variables. R^2, or in-sample predictive power, is the correlation between actual and predicted values and incorporates all estimation data. Table 5 shows behavioral intention (0.734) and e-trust (0.473) R^2. According to Sarstedt et al. (2014), R^2 values of 0.25 imply weak in-sample predictive power, 0.50 moderate, and 0.75 considerable.

Table 5. Structural Analysis Results

Inner Model Assessment	R^2	Adjusted R^2	Q^2	Model Fitness
Behavioral Intention	0.734	0.727	0.654	
E-Trust	0.473	0.471	0.463	
SRMR				0.121
dULS				4.025
NFI				0.794

As suggested by Shmueli et al. (2019) PLSpredict examined the model's out-sample predictive capacity. Predictive relevance evaluates the efficiency of parameter estimates and models in producing observed values, Q^2 values that exceed 0 indicate that the model is considered predictively relevant, while values below 0 indicate that the model is not predictively relevant (Samosir et al., 2023). Table 5 indicates Q^2 values above zero for all endogenous variables, which means this model has excellent predictive power. This study also checked the moderating effect by conducting multigroup analysis on gender. Multigroup analysis using Henseler et al. (2016) three-step PLS-SEM. MICOM found measurement invariance—male and female view measurements similarly. No multigroup analysis was done since the model only met partial invariance criteria. Therefore, multigroup bootstrap analysis compared the two groups' standardised route coefficients. No group had significant structural route differences. Each group's two standardised coefficients must have similar parameters and p-values below 0.05. Tables 6 compare two user groups' expected behavior to three internal indications.

Table 6. Multigroup Analysis Results

Path/User	β		p-value		Invariant
	Male	Female	Male	Female	
Performance Expectancy → Behavioral Intention	0.151	0.142	0.125	0.031	No
Effort Expectancy → Behavioral Intention	0.280	0.092	0.022	0.095	Yes
Facilitating Conditions → Behavioral Intention	0.190	0.414	0.128	0.000	No
Social Influence → Behavioral Intention	-0.018	-0.029	0.439	0.322	No
Social Influence → E-trust	0.706	0.690	0.000	0.000	Yes
E-trust → Behavioral Intention	0.344	0.340	0.004	0.000	Yes

This study examined the influence of performance expectancy, effort expectancy, facilitating conditions, and social influence on the intention to use telemedicine. The study also examined the impact of e-trust on behavioral intention and the effects of social influence on e-trust.

This study rejects the impact of social influence on behavioral intention (β = -0.025, t-value = 0.433, p-value > 0.05, f^2 = 0.001), contrary to Li and Han (2021). This suggests social influence does not affect Halodoc use. The absence of evidence linking social influence to behavioral intention may be because an individual's intention to use telemedicine is not necessarily driven by their desire to be seen as equal. Telemedicine adoption is based on personal needs. Wellness is subjective and everyone has their own method (Firdaus et al., 2023).

The study found a favorable correlation between performance expectancy and behavioral intention (β = 0.126, t-value = 1.918, p-value = 0.028, f^2 = 0.023), supporting Li and Han (2021). Telemedicine systems' usability, efficiency, and reliability directly affect people's desire to use this revolutionary healthcare technology. This data can improve telemedicine user experience and adoption, making remote healthcare more accessible and effective.

The study's findings revealed that effort expectancy positively impacted behavioral intention (β = 0.157, t-value = 2.277, p-value = 0.011, f^2 = 0.032), confirming Li and Han (2021). Since effort expectancy is the perceived ease and convenience of using telemedicine platforms, it positively affects behavioral intention to use them (Amin et al., 2022). This emphasizes the importance of user experience and usability in telemedicine service adoption and suggests that interface enhancements could boost adoption of this revolutionary healthcare technology.

The study indicated that the facilitating conditions positively impacts users' behavioral intention (β = 0.342, t-value = 4.133, p-value = 0.000, f^2 = 0.140). The result supports Rahi et al. (2021). The positive effect emphasizes accessibility, usability, and technical assistance in telemedicine adoption. Telemedicine has the potential to alter healthcare delivery, but enabling conditions must be improved to increase its acceptance and efficacy. Understanding and enhancing these positive qualities will help telemedicine spread across healthcare systems.

The findings indicate that users' behavioral intention is positively influenced by e-trust (β = 0.353, t-value = 4.702, p-value = 0.000, f^2 = 0.150). This study reveals that e-trust greatly influences telemedicine behavior, underlining the necessity to trust online healthcare systems. Healthcare providers and regulators should prioritize e-trust as the digital world transforms healthcare. This can boost patient participation and telemedicine utilization, improving medical access and outcomes.

In addition, the results of this research show that a positive social influence has a significant positive impact on e-trust (β = 0.688, t-value = 13.806, p-value = 0.000, f^2 = 0.899). This study confirms Dewanta et al. (2023). The positive effect shows the importance of interpersonal contacts and community dynamics in online trust-building. This new

knowledge helps us understand e-trust and shows how social influence can boost digital trust-building initiatives, which will benefit digital-age individuals and businesses.

CONCLUSION

This study examines the factors that influence telemedicine use intentions. It illuminates technology adoption patterns by examining UTAUT factors and e-trust in telemedicine. It shows that performance expectancy, effort expectancy, facilitating conditions, and e-trust positively influence people's willingness to use telemedicine for their healthcare needs. However, the lack of a substantial effect of social influence on behavioral intention suggests that interpersonal factors should not be ignored even though they may not directly affect telemedicine adoption decisions. The study indicates a significance indirect effect of social influence on e-trust, providing insights to enhance digital trust-building for individuals and businesses in the digital age.

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