

Extending UTAUT with Perceived Trust and Perceived Risk to Explain Telehealth Revisit Intention Among Young Adults in Jakarta, Indonesia: A PLS-SEM Study

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ABSTRACT

This study examines the determinants of young adults' intention to revisit telehealth services in a post-pandemic developing-country setting. An extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework incorporating perceived trust and perceived risk was applied. Data were collected from 12 September to 31 October 2025 using non-probability purposive sampling, yielding 294 valid responses from young adults who had used private telehealth platforms in Jakarta, Indonesia. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The model explained 63.1% of the variance in behavioral intention. Perceived trust was the strongest predictor of revisit intention ($\beta = 0.391$, $p < 0.001$), followed by performance expectancy ($\beta = 0.241$, $p < 0.001$), social influence ($\beta = 0.169$, $p = 0.006$), and effort expectancy ($\beta = 0.150$, $p = 0.019$). Facilitating conditions and perceived risk were not significant. The findings extend the UTAUT framework to a post-adoption telehealth context in an urban developing-country market. Practically, sustaining revisit intention depends more on cultivating perceived trust through reliable service delivery, transparent data practices, and consistent platform performance than on technical support or direct risk mitigation.

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1. Introduction

In recent years, telehealth has shifted from a supplementary service into an important part of modern healthcare. Before the COVID-19 pandemic, telehealth was used on a limited scale, but restrictions on face-to-face consultations encouraged wider adoption and made remote healthcare more acceptable to patients and providers. Prior studies show that telehealth can improve access to care, reduce travel and waiting time, support appointment attendance, and increase healthcare convenience [1], [2], [3].

Although young adults are generally familiar with digital technology, their continued use of telehealth remains less explored compared with older adults or general population samples [4], [5]. Existing studies have mostly examined the initial adoption of digital health services rather than users' intention to revisit telehealth platforms after prior use [6]. This creates an important gap, because revisit intention may be influenced not only by technological acceptance, but also by users' perceived trust and perceived risk when interacting with digital healthcare services [7], [8].

Previous studies by Aydin and Kumru [5] show that UTAUT-related factors, trust, and privacy risk influence the younger generation's adoption of digital health services. However, these studies mainly examined digital health adoption in a broader context and did not specifically focus on users' intention to revisit telehealth applications. Similarly, Vidal-Silva et al. [9] examined telemedicine acceptance in healthcare networks, but further research is still needed to understand how users evaluate telehealth services in different service contexts, particularly between public and private healthcare settings. This local urgency is underscored by Indonesia's healthcare workforce gap: physician density remains below World Health Organization thresholds in most provinces, and the country needs tens of thousands of additional doctors to close this shortfall, particularly outside Java [10]. At the same time, Indonesia's connected healthcare market is expanding rapidly, with Java-based providers accounting for the majority of digital health activity as platforms substitute for workforce shortages [11]. Since telehealth services in Indonesia are commonly accessed through private healthcare platforms, this study focuses on young adults' behavioral intention to revisit private telehealth applications in Jakarta, Indonesia.

This study specifically adopts revisit intention, operationalized through items adapted from the UTAUT2 continued-usage scale [12], as its dependent construct rather than the related construct of continuance intention. Continuance intention is

typically established through repeated measures of confirmed expectations and satisfaction accumulated across multiple use episodes [13], which this study's single-point cross-sectional survey does not capture. Revisit intention, which reflects a respondent's forward-looking willingness to return to a specific telehealth service, is therefore the more consistent behavioral outcome to model with the data collected here [7].

Based on these gaps, this study examines young adults' behavioral intention to revisit telehealth applications provided by private healthcare platforms by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) with perceived trust and perceived risk. The research framework developed for this study is presented in figure 1.

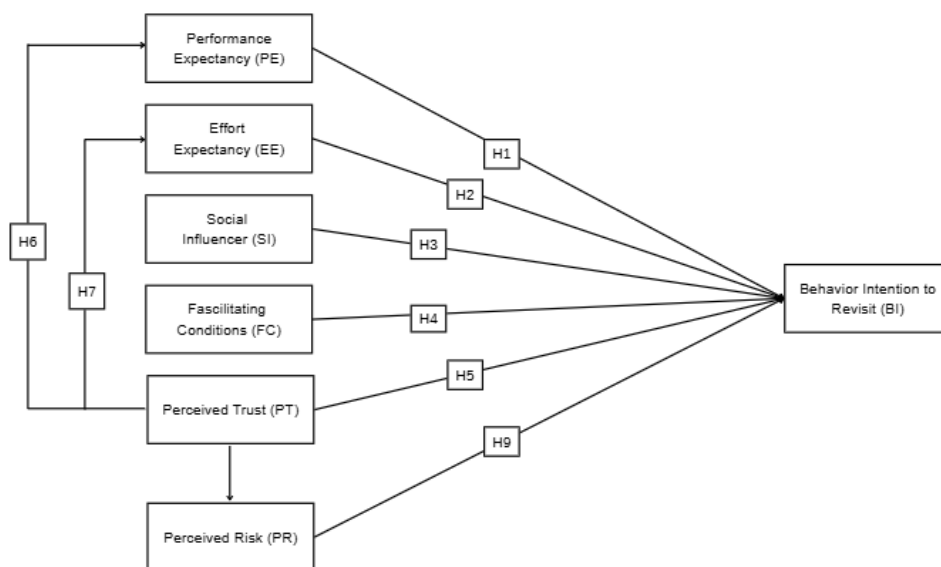


Figure 1. Research framework (adapted from Su et al. [14])

2. Theoretical Background and Hypothesis Development

This study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates constructs from eight earlier technology-acceptance models into four direct determinants of behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions [12]. UTAUT was adopted here rather than earlier models such as the Technology Acceptance Model because it offers a more comprehensive, empirically validated account of adoption behavior across diverse technology contexts, including healthcare [12]. Consistent with prior post-adoption technology studies, this study measures behavioral intention rather than observed use behavior, since intention is an established proxy for continued engagement with a technology [7].

2.1 Performance Expectancy and Behavioral Intention

Performance expectancy refers to the degree to which an individual believes that using a technology will improve task performance. In telehealth, performance expectancy reflects users' beliefs that remote consultation improves access to care, appointment attendance, and health outcomes [3]. Prior UTAUT-based studies on digital health adoption consistently report a positive relationship between performance expectancy and behavioral intention [9], [15]. Accordingly, this study hypothesizes:

H1: Performance expectancy has a positive effect on behavioral intention to revisit telehealth.

2.2 Effort Expectancy and Behavioral Intention

Effort expectancy refers to the degree of ease associated with using a technology [12]. Telehealth reduces the time, travel, and physical effort required to access care compared with in-person visits, which prior studies link to higher continued-use intention [16]. Accordingly, this study hypothesizes:

H2: Effort expectancy has a positive effect on behavioral intention to revisit telehealth.

2.3 Social Influence and Behavioral Intention

Social influence captures the extent to which an individual perceives that people who are important to them believe the technology should be used [12]. In telehealth, encouragement from healthcare providers, family members, and peers has been shown to shape continued adoption decisions [16], [17]. Accordingly, this study hypothesizes:

H3: Social influence has a positive effect on behavioral intention to revisit telehealth.

2.4 Facilitating Conditions and Behavioral Intention

Facilitating conditions refer to users' perceptions that the resources and support needed to use a technology are available [12]. Adequate technical support and device compatibility have been associated with sustained mHealth use in prior research [18], [19]. Accordingly, this study hypothesizes:

H4: Facilitating conditions have a positive effect on behavioral intention to revisit telehealth.

2.5 Perceived Trust

Perceived trust refers to an individual's willingness to rely on a service provider based on beliefs about its reliability, honesty, and competence, even under conditions of uncertainty. In telehealth, trust is particularly salient because users must share sensitive health information and rely on the provider's competence without direct physical verification [20]. Prior research shows that trust not only directly strengthens behavioral intention but also enhances users' performance and effort expectancy by reducing the uncertainty associated with remote care, while simultaneously lowering perceived risk [14]. Accordingly, this study hypothesizes:

H5: Perceived trust has a positive effect on behavioral intention to revisit telehealth.

H6: Perceived trust has a positive effect on performance expectancy.

H7: Perceived trust has a positive effect on effort expectancy.

H8: Perceived trust has a negative effect on perceived risk.

2.6 Perceived Risk

Perceived risk refers to an individual's subjective belief that using a technology or service may lead to negative outcomes, such as compromised data privacy or service failure [21]. In telehealth, this risk is heightened by the need to transmit sensitive health information through remote channels without direct physical verification, and prior studies report that elevated perceived risk reduces intention to adopt or continue using digital health services [17]. Accordingly, this study hypothesizes:

H9: Perceived risk has a negative effect on behavioral intention to revisit telehealth.

3. Research Methodology

This study employed a quantitative research approach using a cross-sectional survey design to collect data from participants at a single point in time.

3.1 Data Collection

Data were collected through direct surveys conducted between 12 September 2025 and 31 October 2025 among young adults aged 18 to 28 years (Generation Z) who had used telehealth applications in the Jakarta area. The survey instrument consists of two parts. The first part captures the respondent's demographic characteristics, such as gender, age, educational background, occupation, monthly income, and the telehealth brand used. The second part measures the variables associated with the acceptance of telehealth, which were derived from prior studies and adapted to reflect the telehealth setting. All indicators were measured using a six-point Likert scale, ranging from strongly disagree (1) to strongly agree (6), allowing participants to express their level of agreement with each statement. A six-point Likert scale without a neutral midpoint was used to encourage directional responses. As all respondents had prior experience using telehealth applications, they were expected to have formed opinions regarding the measured constructs. Therefore, a six-point response format was considered suitable for capturing respondents' evaluations.

3.2 Sample Size and Sampling Technique

The minimum sample size was determined using the ten-times rule. According to Jhantasana et al. [22], the minimum required sample size should be at least ten times the largest number of structural paths directed at any latent construct in the model. In this study, the largest number of structural paths into a construct is 6, thus the minimum sample size required is 60.

This study used a non-probability purposive sampling technique to recruit respondents who met the predefined inclusion criteria. The target population consisted of Generation Z individuals aged 18–28 who live in the Jakarta area and have used a telehealth app at least once. Data were collected via a structured online questionnaire distributed through two channels: the Populix Pop Survey platform and Google Forms. Eligibility screening questions were included at the beginning of the questionnaire, and only respondents who fulfilled all criteria were allowed to complete the main survey.

3.3 Participants

From the distributed questionnaire, 350 responses were obtained. First, one response with missing values was eliminated. Subsequently, as suggested by Ward et al. [23], suspicious response patterns such as straight-lining were removed; 28 straight-lining responses, in which more than 90% of the answers were identical, were identified through spreadsheet analysis and eliminated. Following this, 27 outliers were removed using the Mahalanobis distance in the Statistical Package for the Social Sciences (SPSS) with a significance level of $\alpha = 0.001$. In total, 294 valid responses were used in the analysis, which exceeds the minimum sample size of 60 and therefore supports reliable estimation.

To reduce the potential for common method bias, respondents were assured of anonymity and voluntary participation, and the questionnaire employed validated measurement items adapted from prior studies. Common method bias was further assessed using Harman's single-factor test. The first unrotated factor accounted for 45.84% of the total variance, below the recommended 50% threshold, suggesting that common method bias was unlikely to be a major concern.

3.4 Statistical Analysis

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS to evaluate the reliability and validity of the constructs, as well as to test the hypothesized relationships. The significance of the structural paths was assessed using percentile bootstrapping with 10,000 subsamples and a one-tailed test at the 5% significance level.

4. Results and Discussion

4.1 Respondent Demographics

Table 1 presents the demographic profile of the respondents. Of the 294 valid respondents, 63.27% were women and 36.7% were men. All respondents belong to Generation Z (ages 18–28), with the largest percentage (43.2%) aged 21–25. Most respondents hold a bachelor's degree (61.6%) and are currently employed (55.4%). A detailed breakdown of education, monthly income, and employment is also included.

Because the sample was recruited through purposive, non-probability sampling, the demographic distribution in table 1 also defines the boundary within which the findings can be generalized. The results should therefore be read as characterizing urban, digitally literate Generation Z telehealth users in Jakarta.

Table 1. Demographic characteristics of respondents (N = 294)

Demographic Variables	Categories	n	%
Gender	Female	186	63.27%
	Male	108	36.73%
Age	18 - 20 years old	58	19.73%
	21 - 25 years old	127	43.20%
	26 - 28 years old	109	37.07%
Education	High School Degree	105	35.71%
	Bachelor's Degree	181	61.56%
	Master's Degree	8	2.72%
Income	< Rp.2.500.000	55	18.71%
	Rp.2.500.000 - Rp.5.000.000	68	23.13%
	Rp.5.000.000 - Rp.10.000.000	113	38.44%
	Rp.10.000.000 - Rp.20.000.000	47	15.99%
	> Rp.20.000.000	11	3.74%
Occupation	Students	66	22.45%
	Employees	163	55.44%
	Entrepreneurs	30	10.20%
	Others	35	11.90%

4.2 Reliability and Validity of the Constructs

The reliability, convergent validity, and discriminant validity of all reflective constructs were assessed to evaluate the measurement model, following the guidelines for PLS-SEM analysis [23]. Table 2 reports Cronbach's Alpha (CA), Dijkstra-Henseler's Rho_A (RA), Composite Reliability (CR), Average Variance Extracted (AVE), and indicator loadings, which together provide a comprehensive evaluation of measurement quality.

First, indicator reliability was confirmed, as all loadings exceeded the recommended threshold of 0.70, with values ranging from 0.822 to 0.947, indicating that each indicator shares substantial variance with its respective latent construct. Second, internal consistency reliability was assessed using CA, CR, and RA. The results show that CA values range from 0.780 to 0.923, CR values from 0.869 to 0.951, and RA values from 0.808 to 0.923. All values exceed the minimum recommended threshold of 0.70, indicating a high level of internal consistency. Third, convergent validity was evaluated using the AVE criterion. The AVE values for all constructs range from 0.688 to 0.866, which is above the recommended minimum value of 0.50, confirming that each construct explains more than half of the variance of its indicators.

Table 2. Reliability and validity results

Variable	CA	RA	CR	AVE	Indicator	Loading
Performance Expectancy (PE)	0.872	0.875	0.921	0.796	Telehealth applications assist me with my daily health needs.	0.918
					Telehealth applications help me get my medical needs taken care of more quickly.	0.863
					Telehealth applications have made me more productive in managing my health needs.	0.894
Effort Expectancy	0.898	0.900	0.929	0.765	My interaction with telehealth applications is clear	0.876

Variable	CA	RA	CR	AVE	Indicator	Loading
(EE)					and understandable.	
					Learning how to use telehealth applications is easy for me.	0.883
					I find telehealth applications are easy to use.	0.903
					It is easy for me to become proficient at using telehealth applications.	0.836
Social Influence (SI)	0.905	0.912	0.940	0.840	People around me recommend using telehealth applications.	0.875
					People who are important to me think that I should use telehealth applications.	0.940
					People whose opinions that I value support the use of telehealth applications.	0.933
Facilitating Conditions (FC)	0.780	0.808	0.869	0.688	I have the knowledge necessary to use telehealth applications.	0.840
					I have the tools necessary to use telehealth applications.	0.826
					Telehealth applications are compatible with gadgets I use.	0.822
Perceived Risk (PR)	0.917	0.922	0.947	0.857	I do not believe that telehealth applications are secure.	0.892
					I am concerned about the possible security and privacy risks involved in using telehealth.	0.947
					I fear that telehealth service providers may provide my personal information to others without my consent.	0.939
Perceived Trust (PT)	0.910	0.910	0.937	0.787	I feel that telehealth applications understand my health needs.	0.874
					Telehealth applications seem reliable to me.	0.897
					I do not doubt the honesty of telehealth services.	0.892
					I believe telehealth applications can provide good services and benefits for me.	0.885
Behavioral Intention (BI)	0.923	0.923	0.951	0.866	I plan to continue to use telehealth services.	0.919
					I will try to continue using telehealth services in my daily life.	0.940
					I intend to continue using telehealth applications in the future.	0.933

Fourth, discriminant validity was assessed using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). As shown in table 3, the square root of the AVE for each construct is greater than its correlations with the other constructs. In addition, all HTMT values reported in table 4 are below the threshold of 0.90, providing further support for discriminant validity.

Although all HTMT values were below 0.90, the EE-FC value (0.867) exceeded the stricter 0.85 threshold and therefore requires attention. This relatively high value may be related to the questionnaire items used. The EE items assess whether telehealth applications are clear, easy to learn, easy to use, and easy to become proficient with, whereas the FC items assess whether respondents have the knowledge, tools, and compatible devices needed to use them. These items may be closely related from users' perspective because both concern their ability to use telehealth applications. Nevertheless, the constructs were retained as distinct because the Fornell-Larcker criterion was satisfied, and all indicators loaded the highest on their intended constructs. The PT-PE (0.813) and PT-BI (0.805) values were also examined because they were relatively high, although both remained below the conservative 0.85 threshold. Their relatively high values may reflect some similarity between PT items concerning reliability and perceived benefits and the PE and BI items concerning benefits and continued use of telehealth applications.

Table 3. Discriminant validity: Fornell-Larcker criterion

	BI	EE	FC	PE	PR	PT	SI
BI	0.931						
EE	0.630	0.875					
FC	0.496	0.742	0.829				
PE	0.709	0.679	0.567	0.892			
PR	-0.183	-0.248	-0.248	-0.138	0.926		
PT	0.738	0.680	0.604	0.725	-0.245	0.887	
SI	0.653	0.592	0.467	0.713	-0.179	0.651	0.917

Note. BI = behavioral intention; EE = effort expectancy; FC = facilitating conditions; PE = performance expectancy; PR = perceived risk; PT = perceived trust; SI = social influence. Diagonal values are the square root of the AVE. The same abbreviations apply to table 4 and table 5.

Table 4. Discriminant validity: Heterotrait-Monotrait ratio (HTMT) criterion

	BI	EE	FC	PE	PR	PT	SI
BI							
EE	0.690						
FC	0.565	0.867					
PE	0.788	0.768	0.669				
PR	0.198	0.274	0.297	0.154			
PT	0.805	0.750	0.694	0.813	0.268		
SI	0.712	0.653	0.532	0.800	0.197	0.715	

4.3 Structural Model

The structural model demonstrates satisfactory explanatory power, with Behavioral Intention (BI) achieving an R^2 of 0.631, while Performance Expectancy ($R^2 = 0.525$) and Effort Expectancy ($R^2 = 0.463$) indicate moderate levels, and Perceived Risk ($R^2 = 0.060$) remains low. The inner VIF values ranged from 1.000 to 3.073, with all values below 5, indicating no critical collinearity concerns. The f^2 values indicated large effects of PT on PE (1.106) and EE (0.860), a medium effect on BI (0.155), and small or negligible effects for the remaining relationships. The SRMR values were 0.053 for the saturated model and 0.095 for the estimated model.

Hypothesis testing, summarized in table 5, shows that PE ($\beta = 0.241$, $p < 0.001$), EE ($\beta = 0.150$, $p = 0.019$), and Social Influence ($\beta = 0.169$, $p = 0.006$) have significant positive relationships with BI, supporting H1–H3, while Facilitating Conditions do not show a significant relationship with BI ($\beta = -0.067$, $p = 0.172$; H4 unsupported). Perceived Trust (PT) shows the strongest relationship with BI ($\beta = 0.391$, $p < 0.001$) and significant positive relationships with PE ($\beta = 0.725$, $p < 0.001$) and EE ($\beta = 0.680$, $p < 0.001$), while showing a significant negative relationship with PR ($\beta = -0.245$, $p < 0.001$). PR does not show a significant relationship with BI ($\beta = -0.003$, $p = 0.465$), thus, H9 is unsupported.

Table 5. Structural model and hypothesis testing results

Hypothesis	Relationship	Path Coefficient t	t-Value	p-Value	90% CI [5.0%, 95.0%]	f^2	Inner VIF	Result
H1	Performance Expectancy → Behavioral Intention	0.241	3.407	0.000	[0.125, 0.358]	0.053	2.969	Supported
H2	Effort Expectancy → Behavioral Intention	0.150	2.073	0.019	[0.022, 0.262]	0.020	3.073	Supported
H3	Social Influence → Behavioral Intention	0.169	2.530	0.006	[0.059, 0.280]	0.034	2.247	Supported
H4	Facilitating Conditions → Behavioral Intention	-0.067	0.947	0.172	[-0.175, 0.056]	0.005	2.351	Unsupported
H5	Perceived Trust → Behavioral Intention	0.391	5.325	0.000	[0.267, 0.507]	0.155	2.680	Supported
H6	Perceived Trust → Performance Expectancy	0.725	22.672	0.000	[0.672, 0.776]	1.106	1.101	Supported
H7	Perceived Trust → Effort Expectancy	0.680	19.135	0.000	[0.619, 0.737]	0.860	1.000	Supported
H8	Perceived Trust → Perceived Risk	-0.245	4.538	0.000	[-0.335, -0.157]	0.064	1.000	Supported
H9	Perceived Risk → Behavioral Intention	-0.003	0.088	0.465	[-0.062, 0.052]	0.000	1.000	Unsupported

The PLSpredict analysis was conducted using 10 folds and 10 repetitions. As shown in table 6, all Q^2_{predict} values were greater than zero, indicating predictive relevance for the endogenous construct indicators.

Table 6. Q^2 (PLSpredict) results

Indicator	Q^2_{predict}
BI1	0.493
BI2	0.512
BI3	0.481
EE1	0.341
EE2	0.299
EE3	0.406
EE4	0.345
PE1	0.389
PE2	0.405
PE3	0.451
PR1	0.035
PR3	0.047
PR4	0.049

4.4 Discussion

This study offers critical insights into the primary factors associated with users' intentions to return to telehealth applications. The findings demonstrate that performance expectancy, effort expectancy, and social influence have significant positive relationships with users' revisit intentions, while perceived trust shows the strongest relationship with users' intention to revisit telehealth services.

The notable relationship between performance expectancy and behavioral intention reinforces previously established UTAUT literature, suggesting that functional utility remains important when examining the post-adoption behaviors of Generation Z in Jakarta [9], [15]. For patients, the importance of performance expectancy may reflect the concrete, practical advantages these platforms introduce into their daily lives [9], [19]. Similarly, the significant relationship between effort expectancy and behavioral intention underscores that system accessibility remains relevant to long-term retention. When a telehealth platform is transparent, intuitive, and straightforward, this may be associated with lower cognitive load and a better user experience during stressful health management situations, a finding that aligns closely with previous research [16]. Furthermore, social influence showed a positive relationship with the behavioral intention of younger cohorts. Based on the result, recommendations from trusted peers, family members, and healthcare professionals may be relevant to a younger user's decision to persist with telemedicine, corroborating earlier adoption studies [9].

A central contribution of this research is the prominent role of perceived trust. Perceived trust showed the strongest association with behavioral intention ($\beta = 0.391$, $p < 0.001$) and was also positively associated with performance expectancy ($\beta = 0.725$, $p < 0.001$) and effort expectancy ($\beta = 0.680$, $p < 0.001$), while showing a negative association with perceived risk ($\beta = -0.245$, $p < 0.001$). These findings suggest that respondents who reported higher trust also tended to report stronger performance and effort expectancies and lower perceived risk. However, because indirect effects were not specifically tested in this study, these relationships should be interpreted as separate direct paths rather than as evidence of mediation. This pattern mirrors the work of Kuen et al. [24], which noted that telemedicine adoption is swayed more heavily by trust in the treatment process and the underlying technology than by trust in individual physicians alone.

Intriguingly, perceived risk did not show a significant relationship with revisit intentions, while perceived trust showed a significant negative relationship with perceived risk. While prior literature suggests that risk concerns actively deter intentions to use online medical consultations [17], the current data suggest that perceived risk may be less salient in explaining revisit intention among the post-adoption users examined in this study. In the present sample, trust showed a stronger relationship with revisit intention than perceived risk. Similarly, facilitating conditions did not show a significant relationship with revisit intentions. One possible explanation is that post-adoption users may already possess the requisite digital literacy and physical resources to operate the platforms, which may make external infrastructure or technical support less influential. While facilitating conditions are traditionally documented as vital drivers during the initial adoption phase of telehealth and mHealth systems [18], [19], the present findings suggest that their role may be less prominent in a post-adoption context.

Ultimately, these outcomes suggest that the intention to return to telehealth platforms is more strongly related to trust-centric evaluations than to functional or infrastructural attributes alone. While utility, ease of use, and social networks play supporting roles, perceived trust remains a key consideration in sustained user engagement. For telehealth providers, these insights highlight an urgent imperative: to support long-term user retention, strategies should focus on cultivating and maintaining trust through impeccable service delivery, verifiable clinical outcomes, rigorous data security, and transparent operational communication.

5. Conclusion

This study examined the factors driving young adults' intention to revisit telehealth services in Jakarta, Indonesia, through an extended UTAUT model incorporating perceived trust and perceived risk. The model explained 63.1% of the variance in behavioral intention ($R^2 = 0.631$). Perceived trust was the strongest predictor of revisit intention ($\beta = 0.391$, $p < 0.001$), ahead of performance expectancy ($\beta = 0.241$), social influence ($\beta = 0.169$), and effort expectancy ($\beta = 0.150$). Perceived trust was also strongly associated with performance expectancy ($\beta = 0.725$) and effort expectancy ($\beta = 0.680$), and negatively associated with perceived risk ($\beta = -0.245$). Facilitating conditions and perceived risk did not significantly predict revisit intention.

5.1 Theoretical Contribution

These findings extend the UTAUT framework beyond its conventional focus on initial technology adoption by showing that, in a post-adoption revisit context, perceived trust rather than the four original UTAUT determinants alone is the dominant predictor of continued engagement. By positioning perceived trust as a construct structurally linked to performance expectancy, effort expectancy, and perceived risk, this study offers evidence that trust functions as a central organizing construct within the extended model rather than a peripheral addition, contributing new insight into telehealth acceptance research within a private-healthcare-dominant, developing-country setting.

5.2 Practical Implications

For telehealth providers and digital health stakeholders, these results indicate that sustaining user retention depends more on cultivating perceived trust, through reliable service delivery, transparent data practices, and consistent platform performance, than on strengthening technical support infrastructure or addressing risk perceptions directly. Because facilitating conditions and perceived risk showed no significant direct effect on revisit intention, resources may be more effectively directed toward reinforcing the trust and performance signals that most strongly shape sustained telehealth usage among young adults in Jakarta.

5.3 Limitations and Future Research

While this study offers valuable insights, several limitations highlight important avenues for future research. A primary constraint is the geographic concentration of the sample, which was restricted to young adult telehealth users in Jakarta. Future research would benefit from expanding this scope to include a broader demographic cross section across Indonesia specifically contrasting urban and rural populations. Such cross regional analyses could also clarify how disparities in digital infrastructure, localized healthcare access, and regional cultural shifts impact long term retention. Additionally, because consumer attitudes fluctuate, adopting a longitudinal research design in future studies would allow investigators to track how variables like perceived trust, perceived risk, and revisit intentions evolve or change over extended periods of repeated use. The conceptual model could also be deepened by integrating variables highly pertinent to young adult digital behavior, such as user satisfaction, established habit, e-health literacy, perceived security, privacy concerns, service quality, and price value. Finally, because user expectations vary drastically depending on medical urgency and sensitivity, future investigations should look into specific telehealth niches such as mental health platforms, chronic disease management, dermatology, women's health, or specialized clinical consultations. Distinguishing between these medical fields is crucial, as different clinical contexts may generate different baselines for patient trust, perceived risk, and subsequent revisit behaviors among young adults.

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